Economics Department

Exchange Rate Volatility: The Impact of Learning Behaviour and the Institutional Framework

A Market Microstructure Approach

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Abstract

Traditional macroeconomic models fail to explain short- and medium-term volatility of foreign exchange rates. Following the new strand of market microstructure approaches to the problem, we model the dynamic optimization problem of a monopolistic market maker who faces uncertainty about some fundamental parameter and whose foreign currency position has to be closed by the end of the day. The set-up allows to identify an unambiguously positive effect the institutional framework may exert on exchange rate volatility. Furthermore we find that a simplistic, adaptive learning behavior is a likely candidate for explaining observed pricing patterns. When completed by competition the model reveals incentives to choose less rational ways of behavior.

*Keywords: Exchange rates, exchange rate volatility, learning, market microstructure, market organisation.- I would like to thank Professors A. Kirman and S. Vassilakis, and G. Fernandez de Cordoba for many useful discussions and comments, and Prof. M. Artis for his support.

Contents

1 Idea

We try to explain the commonly observed phenomenon of excess volatility in foreign exchange markets: Exchange rates often are excessively volatile relative to the fluctuations of the economy's relevant fundamentals.

The idea we develop is the following: Traders usually face an uncertain environment in which they try to learn the value of some unknown fundamental parameter in order to improve their optimization behavior. As is well known, there are very efficient ways of learning those parameters such as Bayesian or least squares learning. However, in the course of things we will exclude those behaviors as likely explanations since they simply do not reproduce the kind of volatility we observe in reality.

Instead we assume and will show that adaptive learning behavior is a much more likely candidate for explaining the kind of pricing patterns we observe. It is more likely not only for the degree of excess volatility it is able to create. But - as will be seen in the course of this and a subsequent paper[1] - traders also have a strong incentive to use this updating pattern since it may allow for higher profits than a more efficient updating rule does. For this reason it is not even necessary to refer to the concept of bounded rationality in order to justify the use of a less sophisticated learning behavior. It can rather be argued that traders in financial markets are behaving fully rationally when deciding to apply an unsophisticated learning rule. In other words: Choosing from a menu of different rationality levels the seemingly least rational one can be seen as a sign of full rationality.- If instead one sees the concept of fully rational agents as too unrealistic it is still possible in this framework to argue that agents are boundedly rational and behave adaptively for this reason.

We then investigate how exchange rate volatility is influenced by a change of the institutional framework and, in our subsequent paper[2], by different degrees of competition. It will be seen that the change of a

[1] Wuthe (2000).

[2] ibid.

specific institutional setting - i.e. the length of the trading day in our case - does have an unambiguous impact for all applied variance measures.

Naturally, all of these findings become reinforced or weakened with different levels of clients' sensitivity to price and a changing volume of trade. Also the subjective prior belief and the size of the parameter to be learned show to have a significant impact on exchange rate variability.

The paper will follow the subsequent plan: After an introduction to the foreign exchange market and the market microstructure literature we theoretically model a monopolist in the foreign exchange market and present a menu of possible updating behavior.

In order to see the impact of the updating behavior we simulate this model, starting with a single trading day. This allows us to get a first idea of updating's impact and to see the various variables impact on volatility.

We then look at the performance of the different learning rules in the long run in terms of: Convergence/volatility, stability, and profits. Furthermore we want to see whether there is a "dominant strategy" in the sense that a trader would always prefer to follow one specific updating rule even when competing against other behavioral patterns ('competition' in the monopoly case obviously refers to some kind of rule/performance comparison the trader undertakes by himself).

Finally we check how a change in the institutional setting, i.e. the length of the trading day, influences the volatility behavior that has been detected so far.- We conclude comparing our results with the literature.

2 Some Stylized Facts about Exchange Rates

In this section we are going to give a basic description of the foreign exchange market[3] and present some stylized facts concerning the spot

[3]For the institutional characteristics of this market see further below the section: Institutional Characteristics of the Foreign Exchange Market.

intra-daily foreign exchange rates.[4] These will provide some motivation for the subsequent research.

The foreign exchange market is an international market in which buyers and sellers of currencies meet. The word "meeting" should not be taken literally since predominantly it is a decentralized market in which participants communicate via telephone, computer networks, or telex and are physically separated from each other. It is a 24 hours global market which only over weekends mostly is inactive. While being global through communication technologies there are three main physical centers of activity: Tokyo in Asia, London in Europe, and New York City in America.

With a daily turnover of USD 832 billion in 1992[5] the foreign exchange market is the biggest financial market. This volume has been rapidly growing - it more than tripled over the period 1986-1992 - due to the growing importance of transaction driven short-term investments relative to long-term investments by non-financial institutions. GDDMOP (1994) attribute the quick expansion of intra-daily transaction flows to the development of real-time information systems and to the decrease of transaction costs following the liberalization of financial markets. Short- and long-term transactions in the retail market face a four to five times higher transactions volume in the intra-day wholesale market. This results from the fact that traders reduce their risk with each other through mutual insurance since usually they are not allowed to have open positions overnight.

Spot market operations account for about 64 percent of the total volume of a market-maker's transactions; the remaining part is divided between 24 percent swap transactions, 8 percent futures and options, and 5 percent outright forward transactions.[6] The stylized facts described below focus on the nominal intra-daily spot exchange rates of major cur-

[4]The following presentation draws mainly on: Brock (1996), Flood (1991), and Guillaume, Dacorogna, Dave, Mueller, Olsen, Pictet (1994), hereafter: GDDMOP.

[5]Bank for International Settlements, 1993.

[6]Flood (1991), p.56, figures for 4/1989.

rencies. Experience has shown that well known empirical regularities of daily or weekly data do not always translate into intra-daily analysis (GDDMOP, p.2). It is possible that the different structure of these financial markets is partly responsible for this fact. GDDMOP regard as one of their key-findings the complexity of the intra-day spot market which results from the interaction of heterogeneous agents which differ in geographical locations, risk profiles, and various types of institutional constraints. This heterogeneity contrasts with the homogeneity of market agents which is found at lower frequencies such as daily or weekly data.

It is important to understand what is meant by the term "price" in the foreign exchange market. One has to distinguish between quoted prices, transaction prices, and equilibrium prices. Quoted prices are often reported as 'tick-by-tick' data. These high frequency data are computed as the average of the bid and ask of every observation. Reporting the average rather than taking the bid or ask series as an approximation of the price has the advantage that if the market is adjusting in one direction the directional change of the average price will indicate this clearly, whereas the level of the bid or ask may not if, e.g., a trader skews the spread in order to attract business on a particular side. Transaction prices, on the other hand, may differ from the quoted prices which are indicative only. Indicative quotes are the bids and asks that are posted to all potential customers. Traders usually quote better prices to each other so that actual transactions often take place within and not at the announced spread.[7] Equilibrium prices, finally, are those prices at which demand and supply become balanced.- While in the following we will be concerned with high frequency data the context should always define clearly the intended meaning of the term "price".

Stylized Fact 1: Returns are negatively first-order autocorrelated. This observation is interesting since one would expect the markets to ad-

[7]In highly volatile periods the actual spread can be larger than the quoted spread (GDDMOP (1994)

just to quotes through a series of transactions and, hence, to exhibit positive autocorrelation. Yet, at a very high frequency this is not the case. Several explanations have been offered for this phenomenon: Traders could have divergent opinions about the direction into which a piece of news should affect the market (in other words: Traders are heterogeneous.). Another explanation is order imbalances of market-makers who consequently skew the spread into a particular direction.[8] Finally, as a matter of fact spreads differ between banks - due to different cost structures e.g. - which can cause prices to bounce forth and back between banks.[9]

Fact 2: The amplitude of the spread is positively related to volatility and inversely to the tick frequency. In periods of higher risk such as instances of important news releases market-makers tend to protect themselves with a larger spread. In periods of a low tick frequency such as the closing or opening of markets, lunch breaks, or on weekends the spread widens considerably.[10]

Fact 3: Seasonality. Strong seasonal patterns can be observed for the volatility, the volatility ratio, the directional change frequency, the relative spread, and the tick frequency. The seasonal patterns exist for the hour of the day, the day of the week, and the geographical location of traders.[11] GDDMOP introduce a rescaling of time which shortens periods with little trading activity and magnifies periods with a lot of trading activity. They show that this not only controls effectively for non-stationarities but also support their vision of trader heterogeneity at all time scales.

Fact 4: High System Complexity. The dynamics of the foreign exchange market cannot be explained by a system of relatively low complex-

[8]Bollerslev and Domowitz (1993)

[9]ibid.

[10]Goodhart (1989), Bollerslev and Domovitz (1993), and Mueller et. al. (1990).

[11]Bollerslev and Domowitz (1993), Dacorogna et. al. (1993), Mueller and Sgier (1992), Goodhart and Demos (1990), Mueller et. al. (1990), Guillaume (1994)

ity - even if small stochastic perturbations are present.[12] Investigations into the complexity of the foreign exchange market are motivated by the global unpredictability of foreign exchange rates[13], by the presence of non-linearities[14], and the mixed impact of news on exchange rates.

Fact 5: High short- and long-term volatility autocorrelation. As regards volatility and its clustering in the short-run there is a high autocorrelation or predictability observable. A possible explanation for this phenomenon is the learning process of traders with different priors: After the arrival of important news it may take them a couple of hours of trading before resolving their expectational differences. Long-term memory, on the other hand, may last more than 55 days.[15] A possible explanation here is traders' response to several autocorrelated news arrival processes which correspond to different time-horizons.[16]

Markets' short- and long-term memory can also be found for the spread and the directional change frequency. No explanations have been put forward for the latter observation.

Fact 6: Mixed impact of news. Goodhart (1989) found out that "small" news from Reuters news page have no significant effect on the behavior of foreign exchange rates. The impact of the price formation seems to outweigh the impact of arriving news. Major economic news, on the other hand, such as GDP growth figures, budget deficit, etc. do have a significant impact on the size of exchange rate volatility.

Fact 7: Conditional predictability: While evidence of out-of-sample predictability is generally weak[17] for the short-term it is good if one conditions on the "right information sets". Examples for such informa-

[12]Guillaume (1993).

[13]Goodhart and Figliuoli (1992)

[14]Guillaume et al. (1994a)

[15]Dacorogna et al. (1993).

[16]Haubrich and Lo (1992), GDDMOP (1994).

[17]Diebold and Nason (1990) and Meese and Rose (1990) showed a zero evidence for out-of-sample predictability beyond that of a simple random walk model.

tion sets are: Near-past volatility and volume [18] (predictability increases when near-past volatility and volume decrease); technical trading rules [19]; and lagged volume for near-future returns [20] (price reversals tend to follow abnormally high volume). Evidence of out-of-sample predictability is weak. But there is evidence of good short-term predictability if conditioning is done on the "right" information set. Thus, directional price changes are systematically forecastable conditional on the state of the volatility at different time horizons.[21] Furthermore, volatility on a very short time horizon can be systematically predicted by the volatility on a longer time-horizon, e.g. hourly volatility by daily volatility.[22] As GDDMOP argue, possibly important news first affect middle-term traders (over 1 day) and then trickle down to short-term traders.

Fact 8: Distributional instability. Andersen (1994) and Guillaume et al. (1994a) make use of de-seasonalizing time scales. Their findings suggest that the distributional instability may be due to different information flows and learning processes of traders with differing objective functions. In such an environment it is no longer possible to express all information in the conditional density function of a single stochastic process.

We will now take a look at economic theory and see how it has tried so far to explain the characteristics of foreign exchange rates.

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[18](LeBaron 1992a,b).

[19](LeBaron (1994)).

[20](Antoniewicz (1992, 1993), LeBaron (1992a,b).

[21]Mueller et al. (1994).

[22]Mueller et al. (1994) and Guillaume (1994).

3 Traditional Approaches to Exchange Rate Determination and Their Failure

An impressive literature on asset price volatility, both at a theoretical and empirical level, had been prompted for by erratic fluctuations in stock prices and - since the beginning of the floating period in the early seventies - exchange rates.[23] Traditional approaches to the determination of exchange rates made use of macroeconomic modeling techniques. But while these macroeconomic models explained exchange rate behavior reasonably well in the long-run their short-run forecasts were unsatisfactory.- In the following a brief overview of traditional exchange rate literature will be given in order to help the reader understand better the starting point and basic questions of market microstructure theory.

Within the traditional macro-approach to floating exchange rate determination the monetary model can be seen as the most fundamental one. It considers the exchange rate as the relative price of foreign and domestic money the size of which, consequently, is determined by the relative supply and demand for these moneys (e.g. Mussa (1976)). Different variations can be applied in modeling this relationship such as prices being either sticky or flexible, or the interest rate differential satisfying uncovered interest parity or containing some adjustment for risk. However, empirical testing of the simple monetary model resulted in unsatisfactory outcomes: Coefficient estimates and empirical fit were never particularly good, apart, perhaps, under hyperinflation conditions; high volatility of real exchange rates required an explicit treatment; and out-of-sample forecasts were fairly poor (see e.g. Frenkel and Johnson (1978)).

The empirical observation of a high correlation between nominal and real exchange rates at high frequencies and a low one at low frequencies

[23]For an excellent review of the literature on empirical nominal exchange rate research see Frankel and Rose (1995).

put the assumption of flexible prices into question. In a new approach the latter postulation was given up and goods-market prices were modeled as sticky in the short-run instead. Dornbusch (1976) demonstrated that in the short-run nominal exchange rates may thus overshoot their long-run levels.- Empirical testing of various types of sticky-price models showed mixed success (for a brief overview of the empirical literature on sticky prices see e.g. Frankel and Rose (1995)).

Another approach to modelling exchange rates has been the portfolio-balance model. Its principal difference to monetary models of exchange rates is the assumption that domestic and foreign assets are not perfect substitutes which causes a risk premium to enter the uncovered interest parity condition and the supply of non-monetary assets such as bonds to enter the equation of exchange rate determination. The exchange rate is thus not only dependent on the demand and supply of money but also of domestic and foreign assets. Empirical tests of this literature are surveyed in Lewis (1995).

A further empirical fact remained that was difficult to reconcile with the existing theory: The major part of foreign exchange rate fluctuations could not be explained with net flows of goods and capital that take place between countries. A possible explanation for this observation is that these fluctuations depend on news about the political and economic environment which could imply changes in the future value of a given currency. This idea lead to the notion that the foreign exchange rate is not just the equilibrium price of flow supply and demand over time. Rather it is the price that results from *expectations* of income which can be obtained by holding assets in various currency denominations where expectations are sensitive to those news. Volatility can thus be rationalized by expectations revisions that are induced by new information, i.e. by "news".

Turning to the out-of-sample forecasting ability of fundamental-based models Meese and Rogoff (1983a,b) made a rather discomforting finding: Comparing the out-of-sample forecasting precision of a variety of different exchange rate models they showed that a simple random-walk "model" of exchange rates outperforms more complex structural models at short and medium horizons. This is true even when ex post information on future fundamentals such as money and output is provided to the structural models. Subsequent empirical research has never been able to disprove these findings for the short-run.

Summarizing, it seems that models that try to explain or forecast exchange rates with macroeconomic fundamentals do have little explanatory power or forecasting ability compared to simple alternatives. Furthermore, the findings of Meese and Rogoff (1983a,b), Campbell and Clarida (1987), and Flood and Rose (1993) suggest that this is not just a failure of some specific models but rather that in general no model which is based on fundamentals like money supply, interest rates, inflation rates, etc. will be capable to explain or predict a high part of short- or medium-term exchange rate variability. The difficulty to predict future movements in exchange rates suggests that the information contained in those variables is of limited value only. The striking difference between the volatility of these macro variables and that of exchange rates insinuates the, at least partial, relevance of information extrinsic to the included variables.[24]

Furthermore, the highly aggregative character of macromodels which try to capture all determinants of demand and supply of foreign exchange requires often, in compensation, the adoption of simplifying assumptions such as: Information is perfect, agents are identical, and trading is costless. Since one of the most important implications of these assumptions is the absence of a motivation for trading (which contrasts highly with the high volume of daily transactions observed in foreign exchange markets) one can wonder whether a more realistic specification of the foreign exchange market might solve some of the empirical problems.

[24]Theories of rational speculative bubbles and speculative attacks do allow for some explanation of excess volatility: But they are not capable to show when and why bubbles or attacks begin and end.

4 The Market Microstructure Approach

Relatively little seems to be understood about the short-run behavior of prices and trading volumes in financial markets. Sharp price movements can be observed at times during which those variables which are considered economic fundamentals change very little. While the above described findings could give rise to pessimism versus exchange rate research a new approach has developed which analyzes the market for foreign exchange from a microeconomic perspective - the market microstructure approach. The cardinal difference to traditional modelling is that the exchange rate is no longer considered as a macroeconomic phenomenon. Microstructural analysis rather focuses on the behavior of participants in the foreign exchange market and on the impact of information and institutional rules. I.e., it is concerned with the trading process itself and on how specific trading rules change the equilibrium behavior of prices. At the same time the assumption of identical agents is no longer maintained. In the majority of microstructural models it is implicitly taken as given that market participants are heterogeneous. They do not only differ in such key determinants of economic behavior as wealth, preferences, and information; but beyond the latter also in differences in opinions and beliefs. These heterogeneous agents interact with each other in the market where the specific kind of interaction is dependent on the way the market is organized. This in turn can have important consequences for the evolution of prices.

Studying the microstructure of markets touches the more fundamental issue of how prices are formed in an economy. In standard economic modeling of price determination the equilibrium price is given where supply and demand schedules meet. But relatively little is said about how this equilibrium point is reached and how individuals' different preferences are coordinated. One of the reasons for this is its argued irrelevance: Economic analysis is mainly concerned with states of equilibrium. Therefore properties of equilibrium prices are in the center of interest;

they can be analyzed without considering the actual mechanics through which the equilibrium is attained.[25] This implies however the premise that the actual trading mechanism has no influence on the equilibrium outcome.[26]

Another approach did regard the procedure of price formation but using a fictitious price-setting process: The tâttonement of the Walrasian auctioneer. The market price arises through a series of preliminary auctions in which traders readjust supplies and demands so long until an equilibrium price is found at which no trader wishes to revise his orders any more. No trading is allowed outside equilibrium; the auction procedure is costless so that there are no frictions in the exchange process.- Walras based this price discovery model on the actual mechanics of the Paris Bourse. But while the model helps imagining the process of price formation it is questionable that it captures the actual process of many markets. Markets differ significantly in their organizational set-up. And if trading is more complex than the simple matching of supply and demand the behavior of traders can play an important role.

These considerations lead to specific analyses of the intermediation activity of dealers itself which revealed new aspects of the price process.[27] If, for example, a market exhibits frictions such as a cost of immediate trading then the resulting outcome could in fact be a twofold price depending on traders time preferences for trading. The Walrasian tâttonement, instead, allowed for a single equilibrium price only.[28] Subse-

[25] E.g. in the rational expectations literature this approach to price setting can be identified.

[26] For a discussion of the issue whether the equilibrium discussed in rational expectations models is actually ever attained, i.e. whether there is any trading mechanism that can implement such an equilibrium, see O'Hara (1995), Section 4.3.

[27] The first economists to draw attention to the important role of stock dealers probably were Working (1953), Houthakker (1957), and Baumol (1952). Demsetz (1968), quoted most often, was the first to give a more direct analysis of trading and is therefore said to be the starting point of formal market microstructure.

[28] The Demsetz model will be described in more detail further below.

quent research investigated the impact of different trading mechanisms, specific market structures, and the interaction between these elements and trader behavior.

Before presenting in more detail the modelling approaches to traders' behavior - on which the original research of this paper builds - and their main results a description of the institutional basics of the foreign exchange market will be given.

4.1 Institutional Characteristics of the Foreign Exchange Market

Knowledge of the specific institutional characteristics of a market is important in microstructure theory because one of its principal assumptions is that the particular microstructure of a market affects the evolution of prices.

In order to give a characterization of the foreign exchange market it is necessary to describe its participants, the mechanics of trading, and its auction structure.[29]

The participants in the foreign exchange market can be classified as market makers, brokers, customers, and central banks where market-makers - at commercial and investment banks - make up for the biggest share. They are agents who, upon request, provide a two-way quote, i.e. both buy and sell (bid and ask) prices and thus create or "make" a market. They can do so in one or more currencies. When a market-maker, on the other hand, orders to buy or sell a specific quantity at a specific price from a broker this so called limit order will be kept in the broker's book. Upon demand the broker then quotes the best bid and ask price from this book. While market-makers may trade on their own account this is not possible for a broker. Also, the latter cannot contact any customers. The service they provide rather is one of bringing together

[29]For an introductory overview of microstructure theory and the foreign exchange market see Flood (1991).

market-makers for which they charge a profitgenerating fee.

The other market participants are central banks who may try to move exchange rates or pursue international transactions, and the customers of the market-making banks. Customers usually try to accomplish their transactions in international trade via the foreign exchange market.

As for the mechanics of trading there is a significant difference between transactions in the direct or customers market and brokered transactions: Brokers collect limit orders from market-makers (specified with respect to size and price) which then remain with the broker until another market-maker has been found who is willing to transact at the broker's quote. The brokerage fee is shared by the banks involved in the transaction. In interbank deals, on the other hand, banks contact each other directly and transactions take place without any third intermediary. The bank who is receiving a call quotes a bid and an ask price and acts thus as a market maker without knowing whether the calling party wants to buy or sell a given currency. Quantities traded usually follow multiples of some customary amounts. Payment or so called "value" date of a completed spot deal is two business days later to allow for settlement arrangements.

Confronting these two methods of interbank trading there seem to be a couple of advantages of brokered trades: Order dissemination between market-makers is rather swift; absence of any obligation to provide a market to the counterparty; anonymity in quoting is preserved. This latter quality allows a quoting bank to hide its identity and thus its possible strategic intentions.

Considering transactions with customers it can be noted that they only take place with market-makers but never go through brokers. The reason for this is the latter's difficulty in monitoring a customer's creditworthiness. This task can be accomplished more easily by a bank of which the customer may already be a client. The procedure of customer trading strongly resembles the one of interbank trading: A customer is asking for a quote, and the bank, acting as a market-maker, provides a two-way quote. Again, it is not known to the market-maker whether the potential client intends to buy or to sell. The main difference between customer and interbank trading lies in the fact that a customer will never have to provide a market himself.[30]

From the above description it has become obvious that the foreign exchange market combines two different auction structures: The brokered market and the interbank direct market. While the latter can be characterized as a decentralized, continuous, open-bid, double-auction market, the former can be classified as a "quasi-centralized", continuous, limit-book, single-auction market. The interbank market is decentralized in that price quotations and transactions are happening in exclusive encounters between agents, i.e. usually on the phone. Prices, thus, are not public and other traders have no access to this specific trading opportunity as would be the case in a centralized market. However, the brokered market, on the other hand, cannot be called completely centralized because of the multitude of brokers present there each of whom only stores a part of the total amount of market-makers' limit orders.[31]

Both types of markets are continuous markets as opposed to call markets. This specification refers to the time dimension of transaction consolidation. Trading does not occur at predefined moments in time, the so called "calls", where transaction orders arriving in between two calls are retained until the next call; rather transaction orders are processed immediately as they arrive.[32]

[30]Although foreign exchange market actors also deal for future value date this will not be considered here since it is irrelevant for the contents of this paper .

[31]Differences in the degree of centralization can have an impact on market performance: Centralized trading and price information, as usual for brokerage, can generate gains in efficiency and consequently imply economies of scale. (See e.g. Garbade (1978).)

[32]While most microeconomic models assume call markets (e.g. the Walrasian tâttonement model) the type of consolidation chosen can affect the outcome of a market process. To see this imagine a continuous market where past transactions have satisfied some of the agents. This will cause a shift in demand and supply with

In an open-bid market price information is communicated to all participants in the market. The interbank market is approximating this structure with the important difference that pairing of communicating agents is bilateral only. The market is called open-bid, however, since in principle for every agent it is possible to contact a market-maker and ask for a quote.- Also in the brokered market the contact between market-maker and broker is bilateral. Yet, as was described above, the broker does not fully reveal the contents of his order book but quotes the best bid and ask prices only.

Finally, due to the market-making activity of traders in the direct interbank market always both, bid and ask prices, are quoted on request. It is this characteristic of price quotations to which the term double-auction refers: Prices are provided on both sides of the market. Brokers, on the other hand, aggregate single-auction quotes: When a market-maker gives a limit buy-order, or alternatively limit sell-order, a broker aggregates these respective quotes into two-way inside spreads. It can happen that a broker's book may be empty on one or both sides in which case he will give a single quote only or none at all rather than making a market.[33]

4.2 Modelling of Market Makers' Behavior

While the institutional characteristics of the foreign exchange market are basic to the microstructure literature its main concern is the modeling of market participants' behavior. In the vast existing research two main points of interest can be identified: Explanations of price movements and the bid-ask spread, and market participants' treatment of price informa-

consequent price changes for later transactions. Thus, ultimately, with continuous trading allocations, the price discovery process, and the ultimate equilibrium price can be significantly different from a call market setting. (For theoretical work on this see e.g. Hahn (1984) or Negishi (1962).)

[33]As for the impact of the described market charateristica on market efficiency of pricing and allocation see Flood (1991), pp. 57-60, as an introduction.

tion.

4.2.1 Spread Explanations and Price Movements

Research that was trying to understand how market prices arise had to face a non-trivial problem: The explanation of the phenomenon that in the same market two prices for a single commodity can be observed, i.e. in other words the existence of a spread. Modeling approaches to this problem were complex since a considerable amount of institutional detail had to be included. In principal, three lines of explanations were developed: A spread can arise due to the cost of dealer services, the cost of inventory holding, and/or the cost of adverse selection.[34] We will begin with describing the first motive.

Provision of Liquidity Services It was said above that Demsetz (1968) had introduced the possibility of some cost in trading. This cost did not so much consist in some kind of fee imposed by a market. Rather the difference in time between order placement and execution possibility could impose real costs on investors. For the possibility to buy and sell immediately when desired, without having to face any waiting time, a price had to be payed: A higher buy or a lower sell rate, respectively.

Let us describe Demsetz' ideas more explicitly: In a continuous market with aggregate supply and demand schedules for a security under ideal circumstances investors would meet simultaneously and the market

[34] In what follows the main arguments of the first two motives are presented, concentrating on those aspects that will be of importance in the main part of the paper.

While the adverse selection argument is not described in more detail since it will not be of use later on its basic argument can be summarized along the following line: A market maker confronts two types of traders, liquidity- and information-motivated traders. Both have to pay a spread for the liquidity services offered by the market maker. However, due to their insider information the information-motivated traders can speculate profitably at the market maker's expense. Therefore the latter charges both types a wider spread in order to protect himself from losses to the better informed traders (see e.g. Bagehot (1971)).

would clear at a certain equilibrium price. But while over the long-run the number of sellers and buyers may match, in the short-run, most likely, there will be a coordination problem. Since by assumption the market is continuous and there is no mechanism for holding orders over time there can be a disequilibrium at any given instant if customers who wish to sell immediately cannot find other customers wishing to buy immediately. Such an imbalance will make it impossible to find a market clearing price.

However, following Demsetz, at any point of time there are two demand and supply schedules present in the market: One of those traders who wish to transact immediately, and one of those who wish to transact but without any specific preferences of when to do so. In order to overcome a disequilibrium situation those traders who wish to transact immediately either have to wait or can induce the other group to accept a deal by offering a higher price. The price of an asset thus contains a cost element: The cost of "predictable immediacy". Security dealers who are standing ready to deal on immediate demand produce this service of immediacy or liquidity.

While Demsetz developed this model for the securities market it can easily be applied to the foreign exchange market[35]: If customers of different countries need to convert currencies in a given short period but are not able to communicate with each other without cost they may place their orders with some foreign exchange dealer. The dealers stand ready to trade on immediate demand. Their intention, however, is not to hold the acquired currency but to sell it back to other customers at a later point of time. Selling it back they will charge a higher price in order to profit on their liquidity service. Therefore, the dealers' supply curve lies everywhere above the customers' supply curve. Similarly, their demand curve lies everywhere below the customers' demand curve. The distance between the dealers' buying and selling price is called the bid-ask spread.

[35]For the application to the foreign exchange market see Levich (1979).

The equilibrium exchange rate in this model is given at the intersection of the customers' demand curve and the dealers' supply curve. This is the equilibrium ask-rate for a transaction in which customers wish to buy foreign currency. Similarly, if they wish to sell foreign currency, the equilibrium bid-rate is given at the intercept of the customers' supply curve and the dealers' demand curve. At these equilibrium prices buy and sell orders will match as long as the environment which generates customer orders does not change.

Demsetz thus provided a formal rationale for the spread observable in security and foreign exchange markets. More important, may be, he showed that the price is an outcome of the optimizing behavior of economic agents. Therefore, in order to understand how an equilibrium price arises the behavior of such an agent had to be analyzed. Furthermore, the behavior of a market as a whole can be regarded as the aggregation of individual trader behavior.

Inventory Models At the beginning of inventory model research stood the question of how one could interpret the equilibrium price determining demand and supply schedules when buyers and sellers arrive at different points of time. Or in other words: To which time periods do these schedules refer in such a situation of disequilibrium?

This concern was first addressed in a paper by Garman (1976). In order to capture the temporal imbalances he characterized demand and supply as stochastic processes rather than looking at individual market participants' trading intentions. A monopolistic, profit maximizing market maker then faces the considerable problem to balance his level of inventory and cash in a context in which the flow of buys and sells is stochastic and non-synchronous. His finite capitalization level imposes upper and lower bounds on his allowable inventory. Due to the random walk of market orders bankruptcy, therefore, has a positive probability and can, in a different setting, be equal to one. The important outcome of this problem set-up in Garman's model is that the market maker uses a spread in order to protect himself from certain bankruptcy. His prices he sets at a profit maximizing level such that the order arrival rates are equated.

Garman's approach is interesting in that it shows the complexity of a dealer's price setting problem. But it is too unrealistic in assuming that the dealer can set his prices only once, at the beginning of time. Due to this assumption the inventory plays no role in his decision problem although it is key for the dealer's survival.

The approach taken by Amihud and Mendelson (1980, 1982) proves more realistic. They reformulate Garman's analysis and explicitly incorporate inventory in the dealer's pricing problem. Prices can be dynamically adjusted. They are able to show that bid and ask prices - the same decision variables as in Garman - now depend on the level of the inventory and can thus change over time along with the inventory position.

The dealer faces market order flows of buys and sells that are represented as independent Poisson processes. The arrival rates depend on the ask and bid prices which are the dealer's decision variables. An important difference to Garman's model is that the inventory level is bounded above and below by some exogenous parameters. This eliminates the possibility of bankruptcy since the dealer cannot run out of inventory any more, and it allows to concentrate the analysis on the relationship between inventory and prices.- The dealer's objective is to maximize expected profit per unit time where profits are a function of the expected cash flow per unit time at a certain inventory position and of the probability to be at this inventory level. His resulting optimal bid and ask prices exhibit certain interesting properties: First, the prices are different from each other and thus provide a positive spread. Second, both prices are dynamically adjusted up and down by the dealer in order to control the inventory position: When the inventory level is low prices are adjusted upwards in order to make a customer sale more likely; when the level is high they are adjusted downward to make a purchase more likely.

In this process the spread widens when the inventory comes close to its boundaries on either side. This, thirdly, implies that the dealer has a preferred inventory position to which he intends to move back when departing from it. This position is not related to the underlying security's value but solely dependent on the variability of the order arrival process. The spread depends positively on the deviation of the security inventory from its preferred level. This result follows from the assumption of the presence of the above mentioned predefined upper and lower bounds of permissible inventory levels.- The inventory's role in this model is that of a buffer.

Interestingly, while the spread in Garman reflected the dealer's effort to reduce his failure probability in this model, with its given exogenous inventory boundaries, it is the result of the dealer's effort to maximize profits and thus reflects his market power.

The inventory model approaches described so far were statistical in nature. Characterizing the market orders as stochastic processes allowed to analyze how the market as a whole functions when resolving the clearing problem of disequilibrium situations. Isolating the order flows from individual market participants' trading intentions provided a possibility to focus more closely on how the market clearing mechanism (i.e. the price setter) interacts with the behavior of the order flow.

Yet, in order to give a more realistic characterization of the dealer's trading activity several other elements should be included in the description of his optimization problem. Stoll (1978) and Ho and Stoll (1981), for example, model the dealer's activity as necessarily involving a portfolio risk, and they thus depart from the order-based analysis. Stoll (1978) was the first to develop this intuition. His market maker is a trader like others in the market who is willing to change his optimal portfolio composition in order to supply immediacy services to other market participants. Being risk averse he faces a cost in offering such a service for which he, therefore, asks a compensation. Ho and Stoll (1981) extend this approach from the relatively simple and unrealistic two-period framework to a multiperiod model with stochastic order flow in order to address the intertemporal role of inventory.

Another element which should be included is the special feature of security markets that specialists there face both, market orders and limit book orders. Zabel (1981) and O'Hara and Oldfield (1986) incorporate this element in their research. Furthermore, they both employ a discrete-time multiperiod framework and depart also with this characteristic from the modeling approaches described previously, e.g. the continuous-time multiperiod model of Amihud and Mendelson.[36] This new framework with prices being called out at the beginning of each period allows to incorporate the realistic feature that traders can "hit a quote" by submitting an order. The dealer has to support his price by trading for his own account on demand. Extending the horizon infinitely but dividing each trading day in a finite number of periods allows also for the inclusion of an overnight market where trade settlement can take place independently of order processing.- Subsequent research of Admati and Pfleiderer (1989), Easley and O'Hara (1992), and Suvanto (1993) should continue to use this timing convention.

In the following we will describe in more detail Zabel's approach since it is his model that Suvanto then will translate to the institutional specifics of the spot foreign exchange market. The model applied in the research of this paper will build on Suvanto.

Zabel assumes that a price-maker, like other market participants, is basically interested in his own returns. He therefore chooses prices that maximize his profit subject to his specific market environment. The specialist's horizon consists in an infinite number of trading days where every single trading day is divided into a finite number of trading periods. Prices are announced at the beginning of each period. All trades happening in this period have to be executed at the announced price; the specialist has to absorb any potential excess demand that may oc-

[36]Two other discrete-time models of dealer behavior has been developed by Bradfield (1979) and Bradfield and Zabel (1979).

cur among current limit orders on the book and market orders arriving in this period. Market and limit orders are assumed to be generated by stationary random processes. They are linear in price with additive random disturbance terms. While the random disturbance of market orders is learned only after a price is chosen the book is observed at the beginning of each period containing the current observation of the limit orders' disturbance as its state. In the last period of every trading day the specialist occurs overnight charges on his inventory holdings. Expected profits are then maximized over an infinite horizon, prices and spread being the choice variables.

It turns out that the optimal spread is independent of the specialist's inventory and of the period of the day. It depends only on current period limit order variables responding to periodic opportunities available in the limit order book.- Dividing the discussion of the outcome into two parts, results with and without the presence of the limit order book, the following can be observed: In the absence of the limit order book the choice of optimal prices and the spread become separate activities. Prices are chosen such as to adjust the inventory towards an equilibrium level and, after that, to adjust prices themselves in the direction of a competitive equilibrium price at which expected excess demand equals zero. The spread, on the other hand, is chosen such as to maximize the expected return on the spread. It causes shifts in the equilibrium prices but the above described process of price adjustment is not influenced by this. Interestingly, it can be shown that the optimal spread is identical to the single period monopoly spread. The expected return is independent of the period, the book, and the inventory position.

In the presence of a limit order book additional opportunities for gains are given. While the spread once more is given by the solution to a single period maximization problem it is now, additionally, also dependent on current information contained in the book and can thus vary with the information available. Moreover, the choice of the spread now interacts with the optimal bid and ask prices. Two motivations are counteracting here: The specialist still intends to adjust his inventory position towards an equilibrium, but at the same time he wants to maximize his spread income and capital gains. The outcome of these conflicting motives is an increase in price variances as compared to the case without limit orders.

The complex multiperiod framework of Zabel (1981) is able to identify the different roles of the dealer's choice variables spread and prices and the impact of the presence of limit orders. A surprising new finding is the myopic character of the spread determination and its invariance with respect to the inventory position. Prices, instead, are sensitive to inventory, period, and length of the horizon. Amihud and Mendelson (1980) had shown a similar price adjustment rule, but in their framework the spread depended on the deviation of the security inventory from its preferred level. This outcome, however, was a direct consequence of the assumption of exogenously given limits of permissible inventory levels.

With its discrete time set-up and the assumption of finite periods for each trading day Zabel's model could be considered a suitable framework to be employed for a description of the spot foreign exchange market where quotations are called out before transactions take place and positions have to be closed by the end of a trading day. But in Zabel's model the dealer faces an order flow which consists of both, market and limit orders. This feature is highly characteristic for the securities market but it is not applicable to the foreign exchange market where brokers are the only market participants who accept limit orders. Furthermore, the dealer in the Zabel model maximizes utility over an infinite time horizon which implies an open inventory liquidation date. A trader's horizon in the spot foreign exchange market, instead, is given by the end of every current trading day.

It is Suvanto (1993) who applies a discrete time multiperiod set-up to the spot foreign exchange market. In contrast to Stoll (1978) and Ho and Stoll (1981) he separates the modeling of the trader's dynamic pricing behavior from the supply side aspects. While holding cost considerations of non-interest bearing transactions balances determine the trader's supply behavior his optimal pricing policy is dependent on price-sensitive stochastic customer orders and inventory considerations. In the following we shall concentrate on the description of Suvanto's model of pricing behavior and position adjustment since this is the framework in which our research is constructed.

Suvanto is looking at a risk-neutral monopolist trader who is maximizing expected revenue over a single trading day. Maximization is subject to the constraint that his expected position of foreign exchange is closed at the end of the day (or meets some other exogenously given target). This condition can be interpreted as a requirement of zero net sales over the period under consideration, i.e. a trading day in this case. The trader is facing transactions uncertainty since buy and sell orders are stochastic. The rationale for this construction is that in a discrete time setting the trader sets prices every period in advance and customers then decide whether to buy or to sell at the quoted prices and which quantities to transact.

Net sales thus become stochastic. The maximization problem is for n periods with a finite horizon; information is assumed to be perfect on the current state. This results in an optimal spread that is independent of the inventory position (i.e. the state of the system) and remains, hence, constant through all periods. Its level maximizes the one-period return on the equilibrium volume of trade. Ask and bid prices, on the other hand, contain the current inventory position as an argument and can be decomposed in two parts: One part consists in the one-period equilibrium quotation that remains equal through all periods; the other part contains the difference between current inventory position and target level as its argument and thus causes a dynamic adjustment of prices which directs the expected inventory level gradually towards its desired level. Hence, a long currency position in early periods leads to a downward adjustment of prices during later periods of the trading day.

However, for the dealer it is not optimal to return immediately to a closed position; he tries to avoid large price fluctuations between one period and another since large price adjustments are generally revenue reducing. Under the condition that transaction disturbances are serially uncorrelated the optimal pricing rule implies constant quotations for subsequent periods after the occurrence of an unexpected shift in the position. Thus, expected quotations do not differ between periods which implies that customers have no reason to postpone transactions in expectancy of better future prices. Information-arbitrage efficiency is therefore guaranteed with this kind of dealer pricing behavior.

As for price fluctuations the dealer's behavior implies a reduced volatility compared to a situation where he would try to immediately return to a closed position after an unexpected shift in the position. The pricing rule's smoothening effect on price variations thus reflects the buffer stock property of inventories which was already identified by Amihud and Mendelson (1980).

Suvanto's results can be extended to a horizon of any length, i.e. any number of trading days, as long as the condition of a closed end-of-the-day position remains satisfied. In the case of new information arriving on future net customer demand price quotations are already affected today.- Suvanto also considers the case of the dealer having private information on the sequence of customer orders during the day. In this situation the information becomes fully reflected in the shadow price for the position constraint. In contrast to transactions uncertainty the arrival of new information has an immediate, not dampened effect on prices: They jump immediately and fully in the direction necessitated by the new information. Consequently, volatility augments more strongly than is the case with transactions uncertainty.

The results of Suvanto's model resemble the ones of Zabel (1981) in that the spread is independent of the inventory level or even its expected change, and that it reflects the monopoly power of the dealer. Prices, instead, are inventory dependent and are chosen such as to balance customer orders. Once again, this pricing rule resembles the one developed in Amihud and Mendelson (1980) but differs from their spread due to the predetermined inventory boundaries.

The similarities of Suvanto's results to those of the securities market literature should not be surprising since the foreign exchange market resembles the securities market in many respects. Suvanto's model is simpler though in that it uses less technical and institutional assumptions. He justifies this arguing that limit orders, return uncertainty, agents' perceptions of the true price of an asset, and asymmetric information are less important for the behavior of a spot foreign exchange dealer than they are for a stock dealer's behavior. Price uncertainty, however, is included through the end-of-day position constraint. It guarantees that the trader's position does not move too far off the desired path.

Are inventory models appropriate for describing the foreign exchange market? To give an empirical answer to this question is difficult since in order to formulate any kind of test it is necessary to determine how the dealer's optimal strategy translates into his prices. This is a problem of significant complexity. Furthermore, many theoretical results rely on specific restrictions on the order arrival process which casts doubt over any kind of generalizations. However, one simple prediction of inventory models is that due to inventory effects there should be mean reversion in security prices observable, simply because a dealer will prefer to sell when he is long in inventory and buy when he is short. The evidence on this issue is mixed: As for equity markets Madhavan and Smidt (1991) find little evidence as do Manaster and Mann (1992) for the futures market. But as for the foreign exchange market Lyons (1993) finds evidence for the presence of inventory effects.

Lyons (1995) finds evidence of an inventory effect during the course of the day in addition to the information effect: when the outstanding position is large, traders modify their bid and ask prices so as to discourage further exposure in that direction.

Summarizing one can say that three main motives for the existence of a spread have been identified by the surveyed literature: A "failure" of the market to guarantee a matching of buy and sell orders at all times;

the market power of a dealer; and the transaction cost related motive of dealer risk aversion. Price movements, on the other hand, are in most cases motivated by inventory adjustment considerations. However, an important aspect in the price formation process has not been considered yet: The interpretation of price information.

4.2.2 Information Based Models

Another important aspect in modeling the behavior of participants in financial markets is their treatment of price information. As for the foreign exchange market it is more difficult to say what is information than it is for the securities market. There assets with some intrinsic value may exist about which insiders may have information which is not public, or individual analysts have information on individual corporations. However, already the identity of an agent placing a market order may convey important information. Furthermore, the observation of some transaction taking place provides information to other market-makers and may alter their own pricing behavior. Also, customers placing orders with these market-makers may in turn become affected by this information and change their order behavior as well.

Many models make use of probability distributions that generate order prices in the market. These order prices can either come from stochastic processes exogenous to the market, thus, e.g., creating a 'true' equilibrium price. Or probability models can represent market-makers' subjective believes about prices. It is also possible that the consensus value of a stock given all publicly available information is given by an exogenous random value. But investors do not act directly on this value but rather on their expectation of it (see Gloston and Milgrom (1985)). I.e., objective processes can coexist with subjective beliefs about those processes. Such a subjectivization of the pricing process is important for the foreign exchange market since it allows for the presence of heterogenous agents with differing believes. Modeling of price discovery should strive to include this feature since it seems natural to assume heterogeneity among market-makers. Flood (1991, p.62) argues that the presence of a big number of market-makers and dealing institutions in the foreign exchange interbank market would be superfluous if all participants were identical. Also, as was seen above, GDDMOP (1994) find that traders have different time horizons and thus exhibit heterogeneity.

Individual market participants may try to refine the parameters of their subjective distributions using pieces of new information arriving through the trading process. The study of such a learning activity has attracted considerable interest since it allows to model the dynamic behavior of economic time series under the influence of some form of learning. Conroy and Winkler (1981), for example, are able to show in a Bayesian model how the subjective variances of a market-maker's subjective distribution changes in the course of the learning process. They consider a monopolistic, expected-profit maximizing market-maker who faces streams of buy and sell limit orders. The market-maker holds the believe that reservation prices of buy and sell orders are generated by two independent normal distributions. Given these subjective price distributions he has to set his optimal spread subject to some inventory constraint. Conroy and Winkler are able to show how the subjective variances of the market-maker's subjective distribution shrink when he uses Bayesian learning in order to update his price expectations. The outcome of this learning process is that the market-maker's spread becomes narrower as learning proceeds.

Bayesian learning usually is applied in contexts where the presence of fully rational agents is assumed. This assumption has been put in question, however. As is well known, proponents of this critical view claim that too much information and sophistication is attributed on the part of economic agents to be a realistic description of reality.[37] In fact, an economic environment may become very complex exactly because of the

[37]See e.g. Arthur (1994).

highly sophisticated strategies chosen by its agents. This has led interest to analyses that assume "bounded rationality" on the part of agents. Agents are assumed to follow simple "rules of thumb" when deciding which actions to take. The motivation for this is that the real world is too complicated, and market participants do not have the capacity to perform the difficult optimization exercises involved in maximizing their infinite-horizon payoffs. In the models of this literature agents are boundedly rational in their method of forecasting and decision-making. In choosing their actions they make use of simple and intuitive rules. Their learning behavior is adaptive in that choices are modified over time on the basis of observations of past performance.[38] While an important use for the theory of adaptive learning is that of a selection device for situations with multiple solutions in the following we will be interested in the dynamic processes of learning themselves - and not only the limit points.

The effects of adaptive learning on the behavior of financial time series is being studied in a relatively new line of research. Intuitively, adaptive learning behavior seems to be a strong candidate for explaining excess volatility in financial markets. In fact, many of these learning approaches to financial markets, some of which we are going to describe now, observe a market which does not really settle down, and often moves through apparent changing regimes.- A couple of papers work within a simple but well defined economic framework in which learning is used in order to explore both evolutionary and stability properties. Lettau (1997) studies optimal portfolio decisions of boundedly rational agents. The latter trade in a market where they can decide on how much of a risky asset to hold in each period. Agents are not able to compute the calculations

[38]For an introduction to the literature on bounded rationality and adaptive learning see e.g. Evans and Honkapohja (1992) for a review of macroeconomic models, Marimon and McGrattan (1992) for a review of game-theoretic models, the Symposium: Bounded rationality and learning (1994), and Honkapohja (1993) for a short introduction to basic ideas.

required for expected utility maximization. Instead they learn from observed outcomes of their past investment decisions and revise their next period's portfolio using this observation. The inductive learning process is modelled via a genetic algorithm: Parameters of the agents' strategies are encoded into bitstrings; the bitstrings evolve using a genetic algorithm; the selection process is based on utility payoffs from a sequence of draws of the random asset. In this behavioral set-up Lettau is able to show that agents take decisions that differ from rational equilibrium outcomes: Adaptive agents tend to take on too much risk compared to rational agents. The size of this risk taking bias is a function of the number of market observations used before agents update their investment portfolio. Under certain conditions it is possible that this bias does not vanish as lifetime increases. Furthermore, a response asymmetry can be observed: The portfolio adjustment after negative returns is larger in absolute value than after positive returns. The continual updating of portfolio weights can thus replicate certain data on mutual funds where agents are continually changing portfolio composition.

Timmermann (1993) uses learning in a standard efficient market model based on a representative agent to explain excess volatility and predictability in stock prices. Dividends in this model grow at a constant rate. The agent makes use of standard least squares techniques in order to estimate the dividend growth rate. The intuition for Timmermann's results then is as follows: A higher estimated growth rate compared to the "true" one will cause the stock price to be relatively lower. (This is true since the stock price is computed as the present value of expected future dividends; yet projections for the latter are relatively smaller due to the higher estimated growth rate.) The lower stock price implies higher dividend yields. Learning effects generate a statistically significant correlation between future stock returns and the dividend yield. This correlation comes through two channels: First, the high dividend yield by itself implies a high payoff on stocks. Second, when the estimated growth rate is adjusted to its "true" value, stock prices will increase. Capital gains will thus be higher than in a model with rational expectations.

As for excess volatility of stock prices Timmermann compares a rational expectations model with the learning framework in the aftermath of a shock to dividends. In the former the dividend shock will be reflected in a proportional shock to the stock price. Learning, on the other hand, implies an additional effect on prices since the shock also affects the estimated dividend growth rate. However, excess volatility of stock prices can only be explained by learning if the sample size is small ($n \leq 100$). With an increasing sample size the estimated parameters converge to their true value and learning induced volatility of prices declines.

Arifovic (1996) is explicitly addressing volatility of foreign exchange rates rather than of stock prices. She examines the relation between learning and volatility using an overlapping generations model of exchange rate determination in which agents learn via a genetic algorithm. It turns out that the learning algorithm can induce exchange rate fluctuations that do not occur under rational expectations. In her model agents' policy decisions about consumption and savings are encoded into a bitstring to render them manipulatable by a genetic algorithm. A population of agents is then evolved through time where observed utility serves as the selection criterion. Arifovic is able to show that in this framework exchange rates do not settle down at any known equilibrium but rather continue to bounce around.

Lyons (1991) investigates the role of heterogeneity of traders' beliefs in the foreign exchange market. Novel in his model is that transactions per se play an integral part in the expectations updating process. The ultimate market equilibrium, therefore, is not the outcome of a one-shot trading game, but is achieved only after the market has learned about the individual bits of information. The driving force behind this is customer business which will continue even if a trader finds himself in the middle of the process of learning about others' information. This continuous mediation of transaction requests is a typical feature of the foreign exchange market (remember that a trader in the foreign exchange market always has to quote a competitive price on request). Lyons uses it to circumround the no-trade results of earlier research and makes it become the linking element between diversity of beliefs, volume, and volatility. In his model a greater dispersion of beliefs induces higher trading volume which in turn induces greater volatility. However, if instead it is the greater variability of customer-business rather than the dispersion of beliefs which causes higher trading volume then the latter's effect on volatility is ambiguous.

Brock and LeBaron (1995) have traders experiment with different belief systems. They employ a two-period competitive equilibrium model of trading volume in which traders have a choice of beliefs based upon past performance using those beliefs. Traders modify their strategies in an adaptive way, but on a time scale that is slower than the one of the trading process itself. (Introducing a slow time scale upon which beliefs change is like increasing a trader's probability of staying in a state once he is in that state.) On the time scale of the trading process this leads to positive autocorrelation in volatility and volume.- As Brock and LeBaron point out themselves, a problem with this approach is that a mechanism is lacking which makes large enough masses of traders change to similar enough strategies. Without such a mechanism the cross sectional law of large numbers will cancel out the aggregate effects of such strategy diversity.

The paper by Beltratti and Margarita (1992) shows how in an adaptive learning environment it is possible that from two groups of more and less smart agents the less smart survives in an evolutionary sense. Agents' bilateral trading world is represented in a neural network. Traders meet randomly when a price is proposed and decide if their respective valuations are amenable to trade. Agents differ in levels of sophistication which can be improved by paying some cost. In this set-up Beltratti and Margarita observe fluctuations between the fraction of smart and dumb agents. When the price settles down it no longer pays to be smart, and dumb agents dominate consequently. But this leads to price instabilities which brings back smart agents.

The above described models all show how the presence of adaptive learning behavior leads to outcomes that are different from rational expectations models. They are able to reproduce certain volatility and non-convergence properties known from the empirical evidence in financial markets. Furthermore, they show the possibility of smartness not being selected in an evolutionary sense. In this context it is of interest to look at the results of a series of research by Gode and Sunder (1990). They are able show in experiments with artificially intelligent and zero intelligent agents that the total surplus of double auction markets is already extractable by a zero intelligent behavior. Stronger forms of individual rationality do not increase the total exploited surplus. Zero intelligent agents do only follow the behavioral rule not to pursue trades that are known to incur a loss. They have no power to observe, learn, or remember, and they do not try to maximize profits. They converge to the proximity of the unique equilibrium price. However, this process takes longer as it does with human or artificially intelligent traders and implies more price volatility. Furthermore, they cause the total profits to be distributed across traders in a less even manner. In obtaining these results natural selection plays no role.

Gode and Sunder attribute these striking findings to the structure of double-auction markets. It is the rules of that trading system which causes allocative efficiency independently of agents' behavior. Gode and Sunder (1997) pursue this intuition theoretically in the affirmative.

While Gode and Sunder's work is not explicitly dealing with the learning behavior of agents it is interesting to see it in the context of evolutionary models in which rationality is not selected for in the evolutionary process (see e.g. Blume and Easley (1992) and as a special case DeLong et al. (1992)). In the research of this and our subsequent paper which introduces competition we will compare different behavioral rules of learning which can be assigned to different degrees of rationality. We will show that those agents who are not able to make any progress in learning extract a higher surplus than agents with significantly more efficient learning behavior. This result is not only able to explain persistent volatility behavior in financial markets but it explains also why over the long-run adaptive learning is not outperformed in an evolutionary sense by more efficient learning behavior. The results suggest furthermore that it is not necessary to assume bounded rationality on behalf of the agents; rather it can be a rational choice to adopt a learning behavior that would be classified lowest in a menu of various levels of rationality.

The subsequent work is organized in the following way: The model of a monopolistic trader is presented in the next section. The introduction of learning necessitates the application of simulations which are introduced next. They allow to investigate the role of the model's different parameters, of the learning rules applied, and of a change in the institutional setting.

5 Modelling the Trader as a Monopolist

5.1 The One-Period Model

The one-period model is presented in a fairly detailed way in order to help the reader understand the setting to which the various modifications will be applied in later sections. The foreign exchange dealer as described here finds himself in the fortunate position of being a monopolist in his market. He is facing a flow demand for and a flow supply of foreign currency. Customers are sensitive to the price of foreign currency. Its price s, the exchange rate, is the price of one unit of foreign currency in terms of domestic currency.

However, there are two different types of customers present in the market: One type is characterized by a high elasticity of net-supply, the other type by a low elasticity, all other parameters being equal between the two groups. The two different arrival rates of customers' demand in period t, x_t, can be described as follows:

$$\begin{aligned} x_t^h &= a - c \cdot s_t^a; \\ x_t^l &= a - d \cdot s_t^a, \qquad c > d, \end{aligned}$$

with s^a being the monopolist's ask-rate and the intercept a being equal for both types. The superscripts indicate which type's demand is being described. The parameters c and d stand for the types' respective sensitivity to exchange rates. Seen from the dealer's perspective, customer demand is the same as arriving sell orders.

If the number of low elasticity type costumers in the market is given by $1 - v$, and the number of high elasticity type costumers by v, then total market demand is given by:

$$x_t = v \cdot [a - cs_t^a] + (1 - v) \cdot [a - ds_t^a].$$

It should be noticed that the demand function does not represent always present market orders but rather average arrival rates of incoming orders. These arrival rates are determined by some exogenous macroeconomic environment.

As for the supply side of the market, there are similarly two types of clients present in the market, high and low elasticity ones. Their two different arrival rates of foreign currency supply in period t, y_t, are as follows:

$$\begin{aligned} y_t^h &= b + c \cdot s_t^b; \\ y_t^l &= b + d \cdot s_t^b, \qquad c > d, \end{aligned}$$

with s^b being the dealer's bid-rate, the intercept b again being equal for both types, and c and d representing the two types' respective sensitivity to exchange rates. Customer supply is arriving buy orders from the dealer's perspective. Assuming the same distribution of high and low elasticity costumers as for the demand side total market supply is then represented by:

$$y_t = v \cdot \left[b + cs_t^b\right] + (1 - v) \cdot \left[b + ds_t^b\right].$$

High values of the shift variable a indicate a high level of demand; high values of b a high level of supply. It is assumed that $a - b > 0$, which guarantees that in equilibrium, both, the price and the volume of trade are positive.

At the beginning of each period t (i.e. of each trading session) the dealer, in his position as a market maker, receives a phone call during which he is asked to quote bid- and ask-rates. If the customer decides to sell or buy at the quoted prices the transaction will take place. Note that market demand and supply functions correspond to the monopolist's expectations about their respective *average* levels. In order for equilibrium to hold expectations have to be correct on average, but not at every single moment of time. The quantities the dealer buys, y_t, and sells, x_t, are denominated in foreign currency per unit of time.

In order to describe the dealer's maximization problem the ask- and the bid-rate are redefined in terms of the mid-rate and the half-spread: The mid-rate is given by $s_t = \left[s_t^a + s_t^b\right]/2$, and the half-spread by $z_t = \left[s_t^a - s_t^b\right]/2$. Revenue per trading session is given by the difference between the value of sales and the value of purchases:

$$\begin{aligned} R_t &= x_t \cdot s_t^a - y_t \cdot s_t^b, \\ R_t &= x_t \cdot [s_t + z_t] - y_t \cdot [s_t - z_t]. \end{aligned}$$

The revenue is defined in terms of domestic currency. Note that $[s_t + z_t]$ equals s^a and $[s_t - z_t]$ is equal to s^b. Rewriting the revenue expression in the following way:

$$R_t = z_t \cdot [x_t + y_t] + s_t \cdot [x_t - y_t],$$

it can be seen more easily that the dealer's income is equal to the spread times the volume of trade adjusted for any cash in- or outflow stemming from net sales or purchases of foreign currency.

It is assumed that the dealer is aware of there being two different types of clients present in the market, and that he knows their demand

and supply functions, i.e. all the respective parameters are known to him. However, the dealer has no information about the distribution of high and low elasticity clients, i.e. the value of the parameter v is unknown to him. For his maximization calculus he therefore has to use his subjective prior belief q about the true value v: The subjective belief q_t is the belief the trader holds at the beginning of period t conditional on all information available up to that point of time.

Furthermore, the dealer is constrained to have his expected foreign exchange position closed by the end of the day, or to meet some other position target m^*. A position is said to be closed (squared) if the value of assets denominated in a given currency is equal the value of liabilities denominated in that currency; i.e. the dealer's holdings of foreign currencies are hedged against any unexpected change in the environment which determines the customers' average buy and sell orders. Since for every foreign exchange transaction there are always two currencies involved a dealer's position can be regarded as closed if net sales of these two currencies are equal to zero by the end of the trading day (or whatever period under consideration).

Apart from risk considerations the constraint ensures that the trader will be able to stay in the market over successive periods of trade. If the trader were to do net sales only (which an unconstrained maximization implies) he would loose the possibility to buy foreign currency from his customers and therefore the possibility to make future profits. The change in the trader's foreign currency inventory, m, during one trading session can be described by the amount of net sales of that period:

$$m_t - m_{t+1} = x_t - y_t,$$

where m_t is the inventory at the beginning of period t, and m_{t+1} is the inventory at the beginning of period $t + 1$ (which is the same as the inventory at the end of period t).

The trader will then try to maximize expected profit subject to the constraint that expected net sales are equal to zero:

$$\begin{aligned}
\underset{s_t,z_t}{Max} \quad E_t(\pi_t) &= \left[q_t \cdot x_t^h + (1-q_t) \cdot x_t^l\right] \cdot s_t^a - \left[q_t \cdot y_t^h + (1-q_t) \cdot y_t^l\right] \cdot s_t^b \\
&= \left[q_t \cdot (a - cs_t^a) + (1-q_t) \cdot (a - ds_t^a)\right] \cdot (s_t + z_t) - \\
&\quad \left[q_t \cdot \left(b + cs_t^b\right) + (1-q_t) \cdot \left(b + ds_t^b\right)\right] \cdot (s_t - z_t) \\
&= s_t \cdot \left[\begin{array}{c} q_t \cdot (a - cs_t^a) + (1-q_t) \cdot (a - ds_t^a) - \\ q_t \cdot \left(b + cs_t^b\right) - (1-q_t) \cdot \left(b + ds_t^b\right) \end{array}\right] + \\
&\quad z_t \cdot \left[\begin{array}{c} q_t \cdot (a - cs_t^a) + (1-q_t) \cdot (a - ds_t^a) + \\ q_t \cdot \left(b + cs_t^b\right) + (1-q_t) \cdot \left(b + ds_t^b\right) \end{array}\right] \\
& s.t. \qquad 0 = E(x_t) - E(y_t).
\end{aligned}$$

Simplifying the expected profit function and using the following conventions: $A = a - b > 0, B = a + b > 0, \delta = 2c > 0, \gamma = 2d > 0$, the problem can be rewritten as:

$$\begin{aligned}
\underset{s_t,z_t}{Max} \quad E_t(\pi_t) &= q_t \cdot \left[A \cdot s_t + B \cdot z_t - \delta \cdot \left(s_t^2 + z_t^2\right)\right] + \\
&\quad (1-q_t) \cdot \left[A \cdot s_t + B \cdot z_t - \gamma \cdot \left(s_t^2 + z_t^2\right)\right]
\end{aligned}$$

$$s.t. \qquad 0 = m_t - m_{t+1} - A + q_t \cdot \delta s_t + (1-q_t) \cdot \gamma s_t.$$

The profit maximizing mid-rate and spread result to be:

$$\begin{aligned}
s_t &= \frac{A}{q_t\delta + (1-q_t)\gamma}, \\
z_t &= \frac{B}{2 \cdot (q_t\delta + (1-q_t)\gamma)},
\end{aligned}$$

It can be seen that the dealer's equilibrium mid-rate will be the lower the more HET he believes to be in the market (q_t is bigger than $(1-q_t)$ so that the relative bigger value of δ gets a bigger weight than γ). The equilibrium spread shows to be even more sensitive to the believed in distribution of clients. On the other hand, when demand is high (high a implies high A and high B) the mid-rate will be high and the spread wide. High supply (b is high and therefore A is low and B is high), instead, leads to a lower mid-rate but again to a high spread. This reveals the twofold character of a trader's business: On the one hand he responds to clients' demand for and supply of foreign currency which he tries to balance with his quotations; on the other hand he provides a liquidity service for which he asks a certain price, the spread. The fact that the spread increases with B, the volume of trade, reflects the trader's monopoly position in the market.

5.2 The n-Period Dynamic Model

We now look at a monopolist dealer who tries to maximize his trading income over a whole trading day. In order to imitate real trading conditions we assume that the trader has to have a closed position, m^*, at the end of the day. This does not apply to the single trading sessions during the day, however. The constraint forces the dealer not to simply maximize his profits in each period, but to keep also an eye on his position and to adjust the quotations if necessary: In case of a non-zero inventory the trader will quote a rate different from the equilibrium one in order to attract net sales.- A trading day consists of T trading sessions where T is given exogenously.

The trader's dynamic optimization problem can be formulated in the following way:

$$\begin{aligned} J_t\left[m_t\right] &= \underset{s_t, z_t}{Max} \quad E_t\left\{\pi_t + J_{t+1}\left[m_{t+1}\right]\right\} \text{ (value function)} \\ J_T\left[m_T\right] &= 0 \text{ (terminal value)} \\ m_{t+1} &= m_t - A + q_t \cdot \delta \cdot s_t + (1-q_t) \cdot \gamma \cdot s_t \text{ (system constraint)} \\ E_t\left(m_T\right) &= m^* \text{(terminal state constraint)}, \end{aligned}$$

where $t = 0, 1, ..., T-1$. The profit function is given by:

$$\begin{aligned} \pi_t = \; & q_t \cdot \left[A \cdot s_t + B \cdot z_t - \delta \cdot \left(s_t^2 + z_t^2\right)\right] + \\ & (1-q_t) \cdot \left[A \cdot s_t + B \cdot z_t - \gamma \cdot \left(s_t^2 + z_t^2\right)\right] \end{aligned}$$

The value function $J_t[m_t]$ gives the expected profit from moment t until the end of the day when optimal control is applied at each future moment $t+1, t+2, ..., T-1$. The terminal value $J_T[m_T]$ is equal to zero since no cost is attached to the possible open position at the end of the day.

The sequential pricing rule can now be derived by solving first the optimal quotation for the last period $(T-1, T)$ and then proceeding recursively backward in time [39]. The resulting optimal quotation for each period t - being a function of the inventory m_t - and spread are obtained to be:

$$\begin{aligned} s_t &= \frac{A}{q_t\delta + (1-q_t)\gamma} - \frac{1}{q_t\delta + (1-q_t)\gamma}(m_t - m_*)/(T-t). \\ z_t &= \frac{B}{2\cdot(q_t\delta + (1-q_t)\gamma)}. \end{aligned}$$

Whereas the spread changes only with the different beliefs of each period and otherwise remains constant at the level that maximizes the one-period return the mid-rate is being adjusted in each period in order to steer the position: The dealer quotes in such a way that he can expect to close a fraction $1/(T-t)$ of the eventual open position during the current and the remaining trading sessions of the day. The mid-rate will be below the equilibrium rate if the current inventory positions falls short of the target, and it will be above in the opposite case. Note that the coefficient attached to the open position increases as t approaches the last trading session T. As in the static model mid-rate and spread depend negatively on the trader's belief of the fraction of high elasticity clients present in the market.

In this optimal pricing policy the belief which the trader holds plays a significant role. In subsequent periods he will therefore try to improve the quality of his belief through a continuous learning process. It is this process with subsequent updating of beliefs we are going to look at now.

[39] A detailed solution to the dynamic optimization problem is contained in Appendix 1

5.3 Learning

In order to effectively maximize his objective function the trader has to use the indirect evidence from the order flow to infer what the value of the parameter is he does not know. The learning problem is then solved via the application of a specific learning rule.

Within this model we specify as the information the trader receives a client's reaction to his quoted price. At the beginning of each trading session the trader quotes his bid- and ask-rate upon request. When his quotation gets hit by a client the trader knows that a low elasticity client had been calling. This is true since all the four demand and supply curves are known to the trader, and since the expected demand and supply curves always lie above the low elasticity type's respective curves. I.e.: The optimal quotation will always be too high for the high elasticity type. After the observation of the outcome of the phone call the trader, at the end of each period, updates his prior belief according to some updating rule. The resulting posterior then becomes his new prior. Observing new data in the following periods the updating process continues.

The choice of the updating rule is of considerable importance since the movement of beliefs over time is determined by it. The dynamics of the updating process and its convergence properties will be reflected in the movement of prices. Hence, knowing those properties of the learning rule allows to determine what aspects of price behavior follow from the nature of the learning rule, and which reflect other factors such as dealer-specific preferences or market structure constraints.

While all asymmetric-information microstructure models essentially solve a Bayesian learning model we propose here the application of less sophisticated learning rules. The reason for this procedure is that the chaotic and volatile behavior of intra-day exchange rates together with the negligible impact of news of minor importance (see Stylized Fact 6) suggest the possibility of a less smooth learning process on behalf of the traders. As will be discussed further below applying less sophisticated learning rules does not necessarily imply a lower level of rationality. This argument is relevant in the context of a market where professional traders try to optimize their behavior in order to extract maximal profits.

Following the taxonomy of learning of Milgrom and Roberts (1991) we will make use of 'unsophisticated learning' behavior as opposed to 'sophisticated learning'. The rules associated with this type of learning are 'adaptive learning' rules. I.e.: Individuals take decisions on the basis of past observations only. [40] We will concentrate on this type of learning behavior in the following and present three specific updating rules that fall into the class of adaptive learning behavior. The order of presentation is not by chance; the learning rules are chosen such as to require a decreasing level of sophistication.

5.3.1 Fictitious Play

Fictitious play is a well known type of adaptive learning behavior. While originally introduced as a method of solving normal form games [41] it later on became applied in modeling learning processes.[42] Its mathematical method is rather intuitive and simple: Taking the empirical frequencies of opponents' past strategies agents are supposed to learn about the future choices of their opponents. Translating this concept into the context of our model the updating algorithm, basically, is of the following shape:

$$Prob(Acpt)(T+1) = \sum_t (Acpt_t)/T,$$

[40] Milgrom and Roberts (1991) define adaptive in the sense that every strategy played by a player must not violate a minimum rationality requirement with respect to opponents' previous play. A sophisticated player, on the other hand, would also be forward-looking by anticipating his opponents' past behavior.

[41] See Brown (1951), Robinson (1951).

[42] For examples of applications see e.g. Fudenberg-Kreps (1993 a.1995). However, they justify ficticious play in terms of Baysean learning (Fudenberg-Kreps (1993)) which is not the line of argument we are persuing here.

where *Acpt* refers to a client's acceptance of the quote. In words: The probability of next period's customer being a LET type is equal to the sum of all acceptances up until now over the total number of periods.[43]

Being backward-looking only an important characteristic of this learning rule is its long memory: The set of all past events is perfectly recalled and influences each new probability calculation. The longer history lasts the less weight a single new event attains. This leads to a smoothening of the series of frequencies over time. In the limit, as $T \to \infty$ the $Prob(Acpt)(T)$ converges to the true parameter value v.

5.3.2 Evolutionary Play

Evolutionary play is a theoretical approach that is being used for problems of equilibrium selection and justification in games. Typically, evolutionary models are not considered as describing proper learning processes since no specific learning rule is introduced. Yet, through the evolutionary process some sort of learning is taking place.[44] In the context of adaptive learning it has to be noticed, however, that in evolutionary models opponents change at each stage which renders the record of past plays non-homogenous.

In an environment of evolutionary learning agents typically are self-interested but myopic; i.e. they have a short-horizon in pursuing their objectives. Players are matched randomly. This implies that they have no knowledge about the characteristics of their opponents. Therefore,their actions are best replies against the distribution of the population's strategies rather than that of a single opponent. However, this behavior can be interpreted as a way of formalizing beliefs on the opponent's strategy. Finally, players can mutate over time. I.e. that they can either be subject to random changes, or they can be replaced by members of a new

[43]An explicit specification of initial move properties is omitted here, but will be dealt with in the simulation part.

[44]For a discussion of the connections between learning and evolution see Selten (1991). Weibull (1995) gives a survey of the work in evolutionary game theory.

generation who, not having played before, randomize their strategies.

Kandori-Mailath-Rob (1993) present a 2x2 normal form game which incorporates the above described features in an evolutionary framework. They are able to show that if the game has a unique dominant strategy then it is globally stable,- even in a dynamic context in which agents' rationality is limited. As for convergence to equilibrium Ellison (1993) shows that when the number of elements in a population is high, and individuals have played the game for a sufficiently large number of periods, fast coordination about the risk dominant equilibrium should be expected on their part. As for the evolution of the system the work of Ellison demonstrates that the speed of convergence to the steady state is higher in local vs. global interaction. This is due to the higher probability of being matched with players that are similar to previous matches.

How are we going to apply evolutionary learning to our model? We will have the monopolist make use of different updating rules the success of which he compares via the profit they make after a given sequence of periods. While playing a mixed strategy comparisons of success are done between hypothetical pure strategies (i.e. results of strategies are compared by looking at the hypothetical outcomes when either of the two strategies would have been played purely). According to the relative success of the two strategies relative weights will be adjusted subsequently for the next sequence of plays. Increments of adjustment are given.

The two strategies the trader will make use of are fictitious play and simplistic learning (which will be described in the following section); i.e. the most and the least sophisticated learning rules on our scale are going to play against each other. Convergence should occur if one of the strategies is dominant. The speed of convergence depends on the change of weights given to each strategy. However, if the change is too rapid the end of game could be reached too quickly, i.e. before one strategy really has proven to be fitter in the long-run.

In the case of competition not one trader will apply different rules of learning but different groups of traders will play with different strategies respectively. According to the groups' success members will then switch to another group.

5.3.3 Simplistic Learning

The third learning rule we introduce is the least sophisticated one. In fact, the rule reveals little insight on behalf of an agent in a learning process' sensitivity to the degree of adjustments being used in the updating process. It is for this reason that we call it "simplistic". It is introduced here as a reference point at the lower end of the scale of sophistication.

The simplistic rule simply says, depending on the last observation, to adjust one's belief half the distance between the belief currently held and the maximum (minimum) parameter value possible. I.e.:

$$q_2 = \frac{1}{2} \pm \frac{q_1}{2}.$$

To be more specific, if in our model the trader meets a high elasticity type (HET) (=no deal took place) he increases q_1, his subjective prior belief about the fraction of HET in the market, by

$$\begin{aligned} q_2 &= q_1 + \frac{1 - q_1}{2} \\ &= \frac{q_1 + 1}{2}; \end{aligned}$$

if he met a low elasticity type (LET) he decreases q_1 such that

$$q_2 = \frac{q_1}{2}.$$

The same happens at the end of each period.

It is obvious that with this learning behavior belief revisions take place in relatively big jumps. With a series of equal observations (i.e. acceptances or rejections only) beliefs quickly adjust towards the respective extreme points. One contrasting observation, instead, makes the new belief immediately jump to the vicinity of the opposite extreme. This jump will be the bigger the closer the last prior has been to the other extreme point. While giving such a big weight to the last observation renders this learning process extremely volatile and non-convergent its expected value, however, converges to the true parameter value:

$$E(q_t) = v \cdot (\sum_{i=1}^{t-1} \frac{1}{2^i}) + \frac{q_1}{2^{t-1}}$$

$$\lim_{t \to \infty} E(q_t) = v \cdot \frac{\frac{1}{2}}{1 - \frac{1}{2}} + \frac{q_1}{2^\infty} = v.$$

After having introduced the three rules of updating that will be used in the following we are now going to implement the simplistic one in our model.

5.4 An Explicit Solution For A Three-Period Model With Belief Updating

A specification of the belief updating process is necessary in order to solve explicitly the above presented n-period model. This is done here using the simplistic updating rule as an example.[45] In order to keep computations tractable the time horizon is limited to three periods. Subject to the different possible phone call outcomes in each period there are four possible new believes q_3:

- If in the previous period $q_2 = \frac{q_1+1}{2}$:

$$\begin{aligned} q_3 &= \frac{q_1+3}{4} \quad \textit{if a HET called;} \\ q_3 &= \frac{q_1+1}{4} \quad \textit{if a LET called.} \end{aligned}$$

- If in the previous period $q_2 = \frac{q_1}{2}$:

$$\begin{aligned} q_3 &= \frac{q_1+2}{4} \quad \textit{if a HET called;} \\ q_3 &= \frac{q_1}{4} \quad \textit{if a LET called.} \end{aligned}$$

[45] In the simulation part all three learning rules will become implemented and compared.

As was shown in section 1.2 the general mid-rate solution for the n-period optimization problem is given by:

$$s_t = \frac{A}{q_t\delta + (1-q_t)\gamma} - \frac{1}{q_t\delta + (1-q_t)\gamma}\left(m_t - m^*_{t+1}\right)/(T-t).$$

If assumingly a trading day consists of three trading sessions, $T = 3$, the quotient $(T-t)$ will take the values $3, 2, 1$ through periods 1 to 3. The new inventory position at the end of any period is equal to the position at the beginning of the period minus net-sales of foreign currency, where the inventory position at the beginning of the period in turn is given by last period's initial inventory position minus net-sales and so forth. Following this structure m_3 will be given by:

$$m_3 = m_2 - [A + q_2 \cdot \delta s_2 + (1-q_2)\cdot\gamma s_2]$$

where m_2 is equal to

$$m_2 = m^* + A - \delta \cdot \frac{A}{q_1\delta + (1-q_1)\gamma}$$

and

$$s_2 = \frac{\frac{1}{2}A + \delta \cdot \frac{\frac{1}{2}A}{q_1\delta+(1-q_1)\gamma}}{q_2\delta + (1-q_2)\gamma}.$$

Substituting these expressions in m_3 one obtains:

$$m_3 = m^* + 2A - \delta \cdot \frac{\frac{1}{2}A}{q_1\delta + (1-q_1)\gamma} - \frac{\frac{1}{2}A + \delta \cdot \frac{\frac{1}{2}A}{q_1\delta+(1-q_1)\gamma}}{q_2\delta + (1-q_2)\gamma},$$

and consequently for s_3:

$$s_3 = \frac{A - \left(2A - \delta \cdot \frac{\frac{1}{2}A}{q_1\delta+(1-q_1)\gamma} - \frac{\frac{1}{2}A+\delta\cdot\frac{\frac{1}{2}A}{q_1\delta+(1-q_1)\gamma}}{q_2\delta+(1-q_2)\gamma}\right)}{q_3\delta + (1-q_3)\gamma},$$

$$= \frac{\left\{\begin{array}{c} A\cdot[-(q_1\delta + (1-q_1)\gamma)\cdot(q_2\delta + (1-q_2)\gamma) + \\ \delta(q_2\delta + (1-q_2)\gamma) + \frac{1}{2}\delta(q_1\delta + (1-q_1)\gamma) + \frac{1}{2}\delta^2] \end{array}\right\}}{[q_3\delta + (1-q_3)\gamma)\cdot(q_1\delta + (1-q_1)\gamma)\cdot(q_2\delta + (1-q_2)\gamma]}.$$

With this explicit expression for the 3rd period's mid-rate it is now possible to compute and analyze the variance of the quotation.

Analysis of Variance Depending on which clients will have called the dealer's 3rd period subjective belief q_3 may take four different realizations as was shown above, and his quotations will differ accordingly. In order to assess the quotations' variability and compare it with the fundamentals's variability we will approximate the variance of the mid-rate in the following way:

$$V(s_3) \simeq \left[\frac{\partial s_3}{\partial q}\,|_{q=\overline{q}}\right]^2 \cdot V(q_3),$$

where $\overline{q}$ is the expected value of q_3.

The unconditional variance of q_3, $V(q_3)$, is given by:

$$V(q_3) = \frac{1}{16} \cdot \left[\frac{7}{2}q_1 + q_1^2 + 5\right],$$

if in the previous period $q_2 = \frac{q_1+1}{2}$; and if in the previous period $q_2 = \frac{q_1}{2}$:

$$V(q_3) = \frac{1}{16} \cdot \left[2q_1 + q_1^2 + 2\right].$$

Both variances are changing with q_1. Their possible numerical values range from 0.3125 to 0.59375 in the first case and from 0.125 to 0.3125 in the second case (for values for q_1 of 0 and 1, respectively). The variance of the fundamentals (F) on the other hand is given by the variance of the slopes, which follow a binomial distribution, and can be computed easily:

$$\begin{aligned} V(F) &= v \cdot [c - vc - (1-v)\,d]^2 + (1-v) \cdot [d - vc - (1-v)\,d]^2 \\ &= (v - v^2) \cdot (d-c)^2. \end{aligned}$$

As for proving the presence of excess volatility it has to be shown that $V(s_3) > V(F)$. Plugging in and simplifying the respective expressions we get:

$$\frac{(v-v^2) \cdot [q_3\delta + (1-q_3)\,\gamma]^4 \cdot [q_1\delta + (1-q_1)\,\gamma]^2 \cdot [q_2\delta + (1-q_2)\,\gamma]^2}{A^2 \left\{-[q_1\delta + (1-q_1)\,\gamma] \cdot [q_2\delta + (1-q_2)\,\gamma] + \delta\,[q_2\delta + (1-q_2)\,\gamma] + \delta^2\right\}^2} < V(q_3).$$

Simulations show that for values realistically small for δ and γ excess volatility will always be present.

6 Simulations

6.1 The Simulation Set-up

All the simulations throughout the paper have been programmed in MATLAB. The dynamic simulation system consists of three or six periods which make for one trading day, respectively. In order to analyze the system's sensitivity with respect to its parameter a single trading day model is being simulated. When analyzing convergence behavior in the long run and comparing different learning rules the system is simulated over many trading days.

The model's parameters, intercept, demand and supply sensitivities, and the true distribution of the population, are given specific values at the beginning of each program. Also a value for the trader's subjective prior belief is specified. (The system's sensitivity to these parameters's values is analyzed in the following section.) For the first period the program then computes the optimal mid-rate, spread, and the resulting inventory. At the end of period 1 the program generates the two possible updates of the initial belief. For both possibilities mid-rate, spread, and inventory are then computed for period 2. The procedure is repeated for the third period where now four different beliefs are potential. All different belief histories are traced back in a matrix, and the respective probabilities of occurrence are assigned. This allows the program to compute the different variances at the end of each trading day. Finally, the variance of the fundamentals is computed which allows to compare volatilities and to determine the degree of excess volatility.

6.2 Volatility Behavior under Changing Parameter Values

In the simulations of this section it is investigated how the variance and quotations change with changing values of the different parameters. We look at the quotations' variance as well as at the fundamentals' variance. As for the computation of the quotations' variance we chose the variance between all possible third period quotations. Although in every third period only one realization is observable the chosen statistic reports the variability between all possible observations of a given third period and can such be seen as an indicator of the variability between observable third period quotations over many trading days. In a following paper which deals with competition it will be seen how this variability changes with an increasing number of traders.

While for the simulations of many trading days different learning rules are used and compared for the single day setting the parameters' impact has been analyzed for one learning rule only: the simplistic learning rule. One reason for this choice is that a frequentalist's approach or evolutionary play are more meaningful for an extended number of trading days. The other is that the size of the single day's variance does not differ much with different learning rules. A short example will give an idea about the size of the differences:

Example 1 *With fictitious play and assuming a prior of zero the resulting possible third period beliefs are:* $2/3$, $1/3$, $1/3$, 0, *and the respective quotations are given by:* 2, 2.5, 2.5, 3.33. *The unconditional variance of all possible last period quotations is then equal to* $V = 0.24$ *(assuming a true distribution of the population of* $v = 0.4$*).*

With simplistic learning, on the other hand, and assuming the same prior the resulting possible third period beliefs are: $3/4$, $1/4$, $1/2$, 0, *and the quotations are equal to* 2.22, 3.33, 1.95, 2.66 *which yields a variance of* $V = 0.30$. *Changing the simplistic learner's prior to a value of* 0.5, *instead, yields a variance of* $V = 0.21$.

The example shows that, depending on the prior, the variance can be smaller or bigger with simplistic learning as compared to fictitious play. But in all cases it is considerably higher than the fundamentals' variance which is given by a value of 0.0216 (for the set of parameter values that has been used in the foregoing calculations).- For the following simulations simplistic learning has been chosen as the rule of updating with a prior of $q1 = 0.5$.

For ease of comprehension all results are presented graphically and then described. As a convention the mid-rates' variance is presented as a solid line, the fundamentals' one as a dashed line.

While varying one parameter's value the values of all other parameters are held fixed at the following levels:

$a = 2$, $d = 1.2$, $g = 0.6$, $v = 0.4$, $q1 = 0.5$.

The Impact of the Size of the Intercept A

Observation 1 *The variance of the mid-rate is continuously increasing in the intercept A.*

In the present setting the quotation's variance is always higher than the fundamental's one. Excess volatility is thus always present and growing in A.

In this simulation the intercept is taking on values between 1 and 5. The variance of the fundamentals can be seen as the horizontal line at the value 0.0216. Since it is not dependent on the intercept it remains invariable. The variance of all possible third period quotations in turn is continuously increasing in A. Already at its initial value of 1 it is exceeding the fundamental's variance by 0.0296. The explanation for this result can be found looking at the behavior of the four possible third period quotations in the second graph of the same figure: It is not only the case that they increase continuously in A, being higher the lower the belief about HET clients' presence in the market. But with increasing quotations also their distance from their mean is growing and, hence, the variance.

The Impact of the Size of the HET's Parameter of Price Sensitivity d

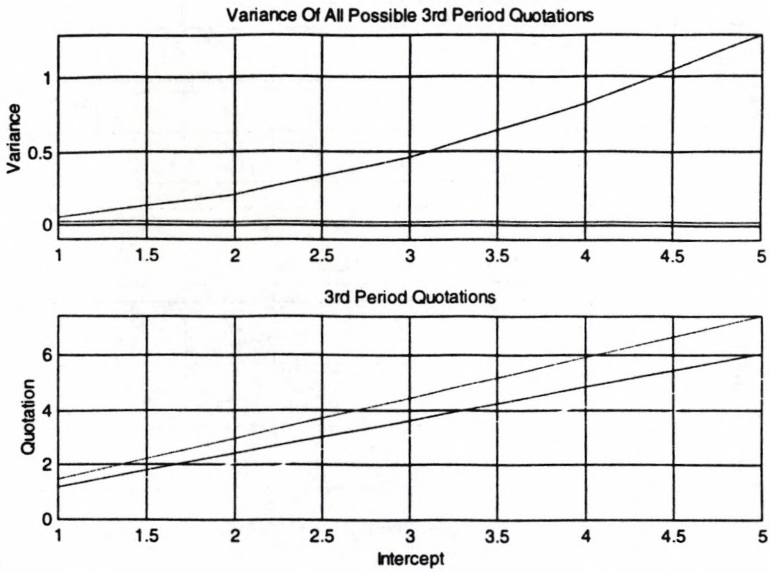
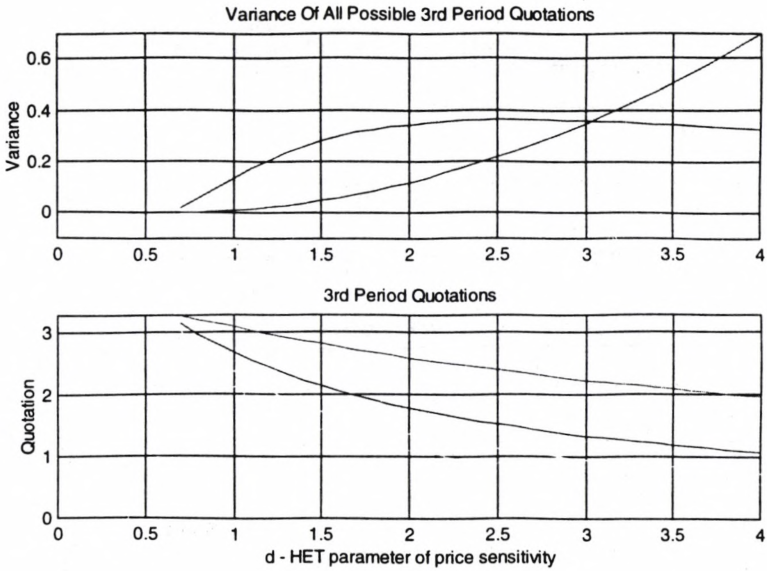


Figure 1:

Observation 2 *The quotations' variance is first increasing in d and then very slowly decreasing. The fundamentals' variance is continuously increasing in d.*

This implies the following behavior of excess volatility in the present setting: It is first increasing and then decreasing in d until, from a specific parameter value onwards, it becomes increasingly negative.



As was shown in the theoretical part of this paper the fundamentals' variance is continuously increasing in the parameter d: At the parameter's initial value of 0.7 the variance has a value of 0.0006; at $d = 4$ it reaches a value of 0.6936. The mid-rates' variance in turn reaches its maximum at $d = 2.6$ and is then slowly decreasing. Both variances behavior together implies an excess volatility which is first increasing, then decreasing, and finally becoming negative at $d = 3.1$.

The graph which depicts the quotations' behavior visualizes the above findings: The quotations decrease with an increasing price sensitivity of HETs. Initially the quotations are very close to each other since the difference between d and g is rather small which renders the impact of different believes about the presence of HETs minor. Different believes matter the more the bigger is the difference between HET's and LET's price sensitivity: Although quotations are falling the distance between the different quotations and their mean is growing and, hence, their variance. This effect is then checked by the quotations' convexity in d which leads to a narrowing of the range of possible quotations and such to a slow decrease of the variance.

The Impact of the Size of the LET's Parameter of Price Sensitivity g

Observation 3 *Both variances are decreasing in g; but the mid-rates' variance is very high for low values of g whereas the fundamentals' variance is hardly affected at all.*

Excess volatility, therefore, is always positive, but strongly decreasing in g.

This simulation reverses the picture of the last one: It starts with a big difference between HET's and LET's parameter of price sensitivity which causes the quotations to be quite different initially. A low price sensitivity of LETs allows the trader to quote very high price - the higher the more the foregoing history made him believe in a high presence of LETs in the market (see the very high quotation of over *eight* which is the quotation of a history of LETs calling only). With the parameters converging also the quotations converge more and more strongly thereby reducing quotations' distance from their mean. This is reflected in a sharp decrease of the quotations' variance whose curve tends to become almost completely flat. The fundamentals' variance in turn is hardly influenced by a change in g: Its decrease is from an initial value of 0.0726 to a value of 0.0006. Excess volatility thus drops drastically with an increase in g, but remains positive throughout in the present setting.

The Impact of the Size of the Prior Belief $q1$

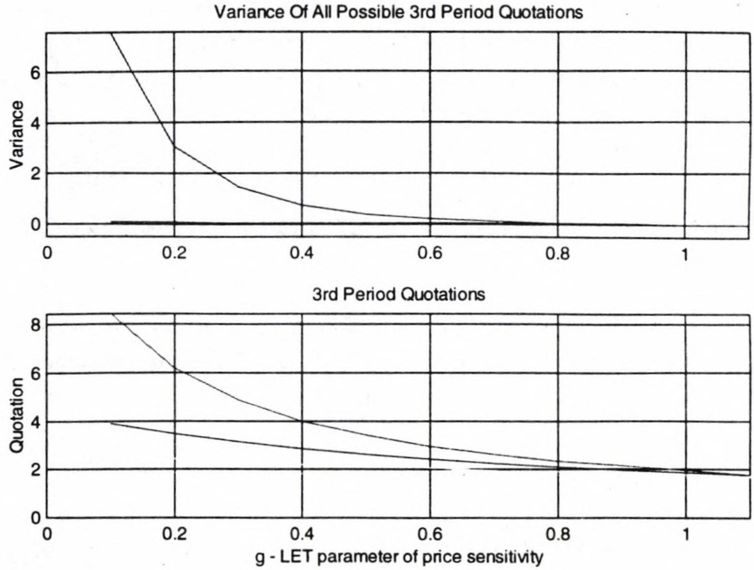


Figure 2:

Observation 4 *The mid-rate's variance is continuously decreasing in the subjective prior belief. The fundamentals' variance remains unaffected.*

Excess volatility is decreasing in the prior belief but is always positive.

In this simulation the possible values for the subjective prior belief range from $q1 = 0$ - the belief that no HET is present in the market - to $q1 = 1$ - the belief that no LET is present in the market. A look at the quotations' graph, however, reveals that the impact is less strong than one would expect intuitively: Quotations are continuously decreasing in

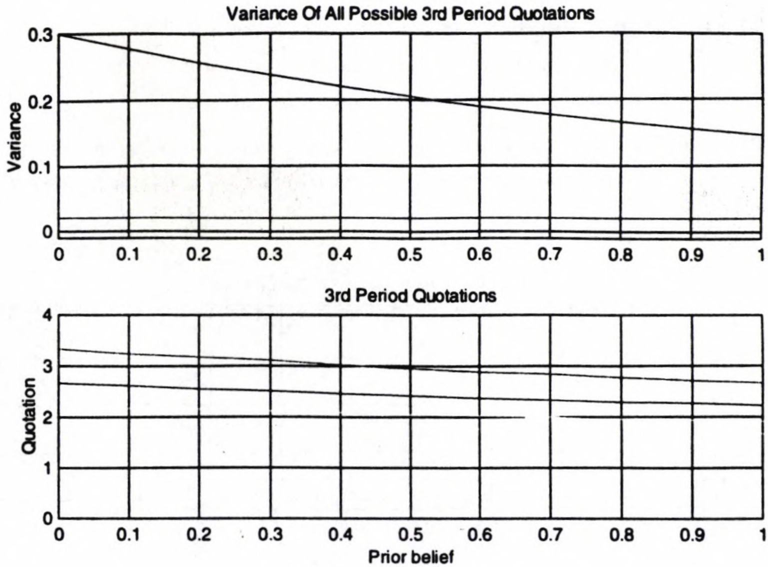


Figure 3:

$q1$, but only to a rather small degree. The reason for this phenomenon is to be found in the trader's updating rule: His halfening of distances between belief and *zero* or *one* leads to a rather quick elimination of initially big differences in possible prior beliefs. For example: Assuming a history of one HET calling in each period the trader's third period belief will be 0.875 with a prior of 0.5, and 0.975 with the extreme prior of 0.9. I.e.: The initial difference of 0.4 between the priors becomes quartered in two periods only.

For the above described effect on the quotations the variance is decreasing in $q1$, but not strongly. Excess volatility remains strongly present throughout the entire simulation.

The Impact of the Real Distribution of the Population v

Observation 5 *The more equal is the population's distribution between HETs and LETs the higher is the fundamentals' variance. The mid-rate's variance reaches its maximum at* $v = 0.4$.

Excess volatility follows the mid-rate's behavior and is always positive apart from the endpoints where obviously it has to be zero.

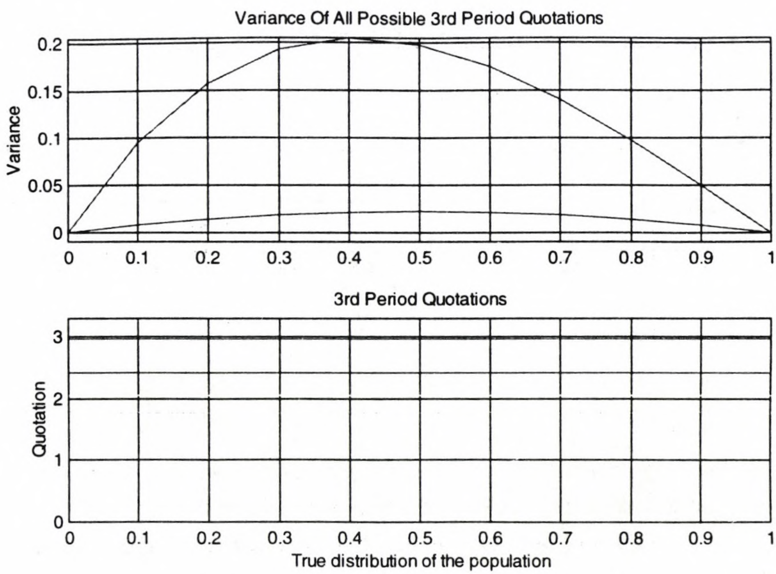


Figure 4:

The quotations are not influenced by the population's true distribution; they only depend on the subjective believes. The variance of the quotations, however, does depend on v since it is the latter parameter which determines the probabilities with which the possible histories and, hence, different quotations occur. While the fundamentals' variance reaches its maximum at the point of equal distribution of the two types, at $v = 0.5$, the mid-rate's variance has its maximum at $v = 0.4$. This difference of maxima depends on the distance between g and d: The further d moves away from g (i.e. if the size of d is big relative to g) the stronger the two maxima differ. The variance, thus, is bigger when nature puts a smaller number of HETs in the market since their price sensitivity is relatively high. (The difference between maxima is growing to the left only because $g < d$ always.)

Due to the bigger dimension of the mid-rates' variance with respect to the fundamentals' one excess volatility has its maximum at the same point as the former variance.

6.3 Conclusions of the Single Trading Day Simulations

The foregoing simulations show that excess volatility of exchange rates can be generated with the theoretical model developed in the first part of this paper. The quotations' volatility, whether excessive or not, is due to the trader's effort to extract information from the incoming phone calls and to learn the true distribution of the population. If, instead, he always used one and the same arbitrary belief, even if it were not correct, exchange rate volatility would be equal to *zero*: All quotations throughout all periods would be equal (assuming an inventory of zero in all periods). This implies that also a variance computation referring to all **observable** quotations would give the same result, i.e. it would be equal to *zero* because of equality of all quoted prices.

Excess volatility is present for a wide range of parameter constellations. The degree of excessiveness depends strongly on the size of the different types' price sensitivity, more precisely: On the relative difference between the two parameters concerned. Although it may appear surprising at first sight that exchange rate volatility is increasing with higher values of HET price sensitivity (and lower values of LET price sensitivity) the finding becomes intuitive if one looks at the underlying mechanism at work, i.e. the changing relative difference between the two parameters. It is evident that bigger differences in price sensitivity necessitate bigger differences in prices and, hence, a higher volatility.

The degree of volatility's excessiveness also depends on the volume of trade: In the context of this model price variability, and hence uncertainty, increases with a higher volume of trade, even without having any new information flowing into the market.

The impact of the true distribution and the subjective prior belief is relatively smaller but still significantly big. The simulations with a varying $q1$ seem to indicate that a higher level of traders' initial degree of informedness is not of high importance in order to check exchange rate volatility in the current setting: As long as information is not sure, or believed as sure, and learning has to take place it does hardly matter how far or close the prior is to the true value of the distribution.

6.4 Analysis of the System's Long-run Behavior

We now turn to the task of investigating the system's long-run behavior. We are especially interested in finding out whether quotations and variances do converge at some point in time. I.e.: Does continued learning over many trading days and weeks lead to finding the true value of the population's distribution and how does this affect the quotations' variance? Furthermore we would like to know whether and how these results change with different learning methods: Can convergence be achieved in a quicker way with more sophisticated learning methods, and will excess volatility be smaller in the pre-convergence periods?

In order to achieve this task the simulation models have been modified in the following way: At the end of each trading day's last period another updating takes place - according to the new information that is available with the last phone call received in period three. This end-of-the-day belief is then being used as the initial belief of the following trading day.

However, at the beginning of period three there are four possible histories each of which will be updated. At the end of the first trading day there are such eight possible histories. Tracing all possible histories over many trading days leads to an explosion of the computational task. For this reason a random device has been programmed which in each period helps selecting **one** of the possible histories in a realistic way. The random device follows the distribution of the population and imitates such the likelihood of receiving a phone call of one of the two types. At the beginning of each period this device determines then whether the previous period's belief (or the prior in case of period two) will be updated or "downdated". For the computation of the variance this implies that no longer the variance between all possible third period quotations is being computed but the variance between all observable quotations of one trading day.

As for the simulation of different learning methods a description will be given at the beginning of the respective sections.

The parameter values used in the following simulations are the same ones as in the ceteris paribus setting of the single trading day simulations, i.e.:

$a = 2$, $d = 1.2$, $g = 0.6$, $v = 0.4$, $q1 = 0.5$.

Volatility Behavior and Convergence with simplistic Learning
The learning behavior implemented in this simulation is the same one as for the single trading day simulations: Depending on which type of client calls the distance between the current belief hold and either the upper or lower end of the distribution's interval will be halfened. The programmation changed in so far as now, at the end of each period, it is the random device which determines in which direction the updating is taking place rather than that all possible paths being followed.

Observation 6 *No convergence of the quotations' variance, the beliefs, or the quotations themselves is observable for a period of 100 trading days.*

Volatility is almost always excessive. The magnitude of oscillations can even be increasing in later stages of a simulated period.

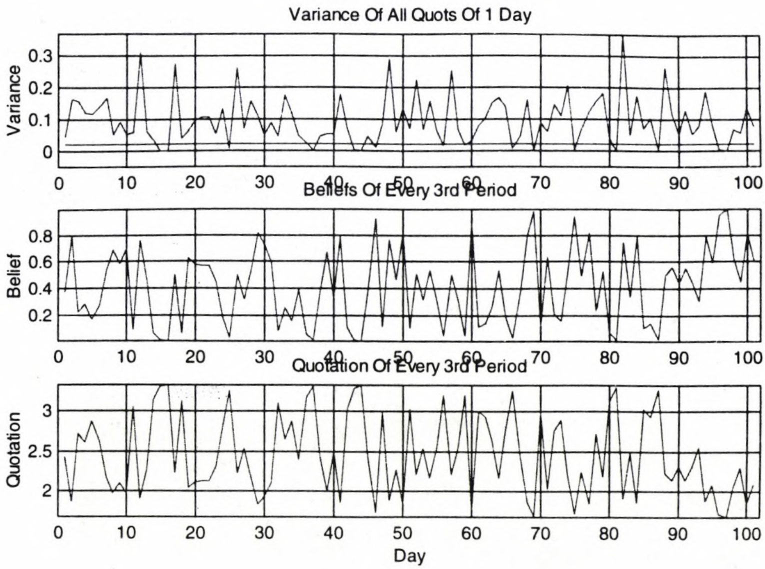


Figure 5:

The three graphs of *Figure 5* depict for each day, respectively, the variance between all observed quotations of one day, the beliefs of each third period, and the quotations of each third period. The quotations are the mirror image of the respective beliefs: The more HETs the trader believes to be present in the market the lower is his quotation. There is no indication that the beliefs, and hence the quotations, do converge over time in the present history of events. Graphs for the other two period's beliefs and quotations have not been reproduced here, but the above described pattern is repeated there.

The fundamentals' variance is depicted as a dashed line in the first graph. Since it is unaffected by the belief updating process it remains at its level of 0.0216 throughout the hundred trading days. It can be seen that the observed quotations' variance exceeds the fundamentals' one in almost 90% of the cases. In the current simulation's history of events the magnitude of excess volatility is even increasing during the second half of the time span. The latter outcome cannot be generalized, though, since it is only due to the specific realizations of the random variable.

The mean profit of the monopolist over a single trading day is equal to 9.42 foreign currency units where the mean is taken over the hundred trading days' total daily profits. The mean spread is given by 5.5642 currency units.

Volatility Behavior and Convergence with Fictitious Play Fictitious play has been implemented in the simulation program in the following way: The random device determines whether the trader's initial belief is equal to *zero* or to *one*. In the following periods, each time a HET calls (i.e. $random\ device \leq v$) one unit is added to the numerator and denominator of the belief variable, in case of a LET calling one unit is added to the denominator only. I.e.: updating takes place according to the frequency with which a HET is calling.

With this different updating behavior the picture changes drastically and we have

Observation 7 *The trader learns the true distribution approximately within the first 20-60 trading days.*

Excess volatility is present for a few instances only. Volatility drops to zero within a few trading days.

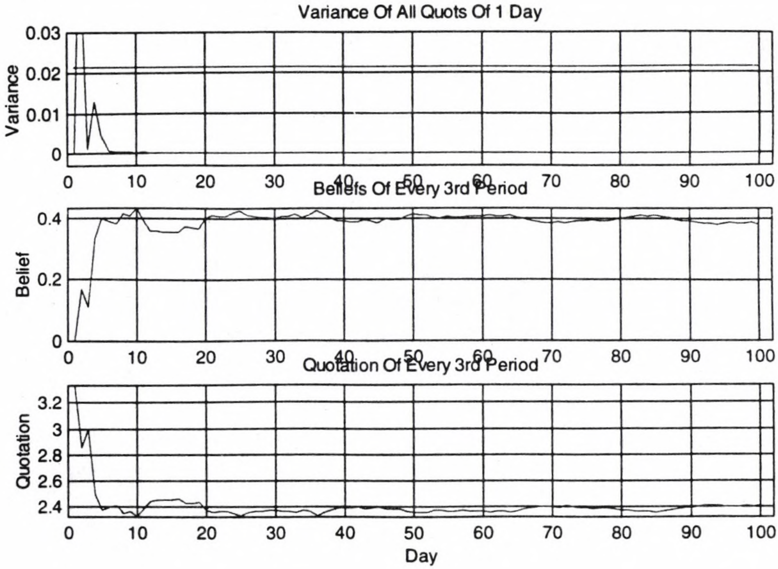


Figure 6:

Two examples of possible one hundred day histories have been reproduced here in order to give a better idea of the typical characteristics the history of events with fictitious play.

Interestingly, in both examples the variance drops very quickly to *zero*, within a few days only. But it can take the trader significantly more time to learn the true distribution approximately. *Figure 6* is an example of the trader learning the true distribution very quickly: His prior happens to be $q1 = 0$. The following sequence of phone calls with mainly HETs calling have his beliefs circle around the true value of the distribution already from the fifth trading day onwards. Consequently, from then on the quotations fluctuate within a small margin around a

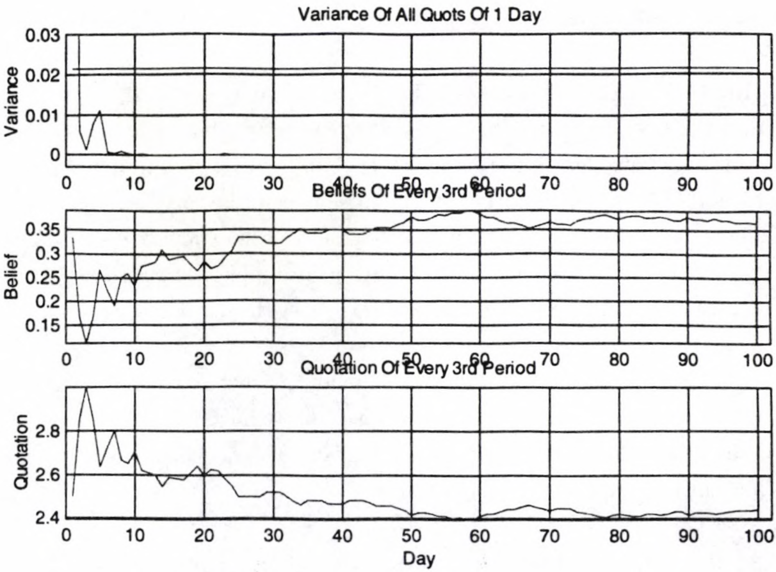


Figure 7:

certain value, 2.4 for our specific parameter set. The variance, reflecting these events, drops considerably quickly and reaches *zero* at the twelfth trading day. Excess volatility is present in one instance only during these days.

In *Figure 7*, instead, we see a trader who takes much more time to learn the true value approximately due to the sequence of phone calls reaching him: The trader's initial belief happens to be equal to one, $q1 = 1$. In the following periods it is only LETs calling him which leads him to believe at the end of day 3 that no HET is present in the market. A changing sequence of HETs and LETs calling let him then change the direction of updating and slowly approach the true value. Only from day 50 onwards his beliefs begin to circle around the true value v. The trader's quotations reflect this process and remain close to 2.4 from day 50 onwards.

However, again the variance is excessive only once and drops to *zero* within the first twelve trading days. The reason for this is the mid-rates dimension: Even during the first days the difference between quotations of subsequent periods is rather small: In a series of hundred simulations the biggest difference of first day quotations has been equal to ~ 0.7; the biggest difference of second days quotations dropped already to ~ 0.19. The quotations' difference to their mean reduces thus at a very fast pace, and the variance drops quickly to *zero*.

The mean profit of a single trading day in this last case is 12.53 currency units. It is considerably higher than the mean profit under simplistic learning. The mean spread is given by 5.41 which lies slightly below the spread with simplistic learning.

Volatility Behavior and Convergence with Evolutionary Play

In the following simulation learning takes place in an evolutionary way: As described above the two different learning rules simplistic learning and fictitious play are being played against each other. Since the trader is a monopolist in the market he has to check a learning rule's success by some method different from a comparison with other market participants' success, i.e. he has to hypothetically play both rules himself and compare their outcomes.

In order to implement this task the following way has been chosen: The trader does his updating throughout the day according to both learning rules. Each new period-belief is then a weighted average of the two differently updated beliefs. The rules are given equal weight initially (during the first trading day). At the end of each trading day one rule's success is being compared with the other rule's success. More specifically, the monopolist computes the profits he would have made using either of the two rules as pure strategies. He then adjusts the weights incrementally according to the two rules' relative success. The new weights will be applied over the entire new trading day. This process carries on until one of the two rules has a weight equal to *zero*. Then the more successful strategy will be played forever. Convergence thus happens with necessity since with an infinite series of random events one of the two limit points will be reached. As for the speed we will have to look at the simulation results.

However, we could also define the play in a different way: Arrival at one of the two limit points does not necessarily imply an end of strategy comparison. The monopolist could carry on comparing hypothetical profits with either of the two pure strategies. If he finds one of the two more successful he will start again to give some weight to it. To check every once and while one's strategy is not an unrealistic characterization of human behavior.

It is this latter set-up that has been implemented in the simulation program. Conveniently, the first interpretation builds a subset of the latter and can thus be easily observed, too.

Observation 8 *Convergence of beliefs, quotations, and the variance happens but is not globally stable. Convergence to fictitious play usually appears during the first 100 trading days.*

The size of initial excess volatility depends on which learning rule has the relative bigger weight and on its relative size. But with a weight of fictitious learning between zero and 1/2 excess volatility will always be lower on average than with pure simplistic learning.

$$\begin{aligned} GG = {} & 21, 22, 23, 24, 25, 24, 23, 24, 25, 24, 23, 22, 21, 22, 21, 20, 21, 22, 23, 22, \\ & 23, 22, 23, 22, 23, 24, 25, 26, 27, 26, 27, 28, 29, 30, 31, 30, 29, 30, 31, 32, \\ & 31, 30, 29, 28, 27, 28, 29, 30, 31, 32, 31, 32, 31, 30, 31, 30, 31, 32, 33, 32, \\ & 33, 34, 35, 34, 33, 32, 33, 34, 35, 34, 33, 32, 31, 32, 31, 32, 33, 34, 35, 34, \\ & 33, 32, 33, 32, 31, 30, 29, 30, 31, 30, 29, 28, 29, 28, 29, 30, 31, 32, 31, 30. \end{aligned}$$

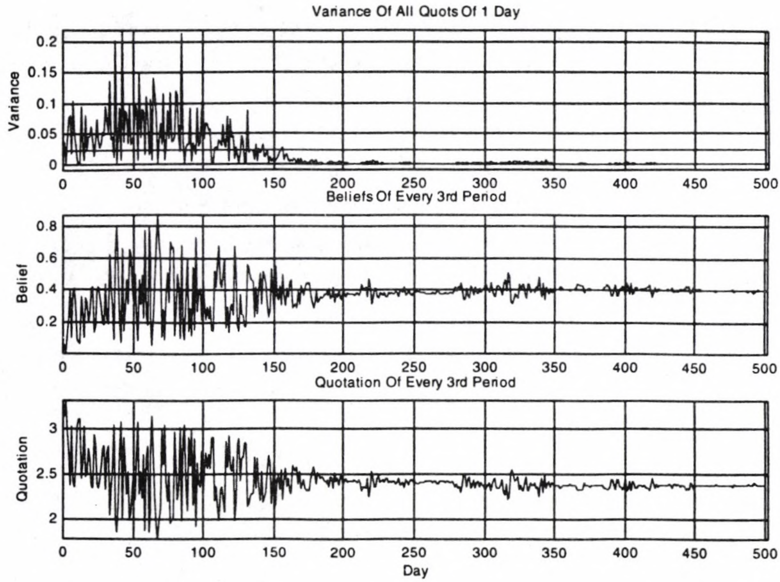


Figure 8:

Once again two examples are represented. The first graph shows a history where fictitious play gains more and more weight. However, for a relative long period, the first 150 days, simplistic learning is very strong, and the picture resembles the one of simplistic learning with oscillations being smaller and volatility being excessive. Then fictitious play begins to rapidly gain more weight which results in a convergence of quotations and beliefs to the true value of the population's distribution. In order to understand the learning process better below the figure the values of the parameter GG have been reproduced for the first 100 trading days. This parameter represents the weight simplistic learning has during every trading day. The total weight is equal to *forty*; during the first day both rules have an equal weight of *twenty*. It can be seen that during the first 100 days the evolutionary process seems to favor simplistic learning. But the process is fluctuating strongly. Convergence of belief and quotation takes only place later on when fictitious play has the full weight. While volatility remains constantly close to *zero*, beliefs and quotations depart immediately from the equilibrium value when simplistic learning begins to take on more value again.- With evolutionary play a trading day's mean profit equals 11.82 currency units compared to the pure strategy payoffs of 9.47 and 11.98 of simplistic and fictitious learning, respectively. It is thus only slightly smaller than the latter's strategy payoff which can be attributed to the initial learning phase with simplistic learning being very strong. The mean spread is given by 5.46.

$$
\begin{aligned}
GG &= 0,1,2,3,4,3,2,1,2,3,4,5,6,7,8,9,10,11,12,13,\\
&\quad 12,11,12,13,12,13,12,13,14,15,16,17,16,15,14,15,16,15,14,13,\\
&\quad 12,13,14,15,14,13,14,13,12,11,10,9,8,7,6,5,6,5,6,7,\\
&\quad 8,7,6,5,6,7,8,7,6,7,6,5,6,5,4,3,4,3,4,3,\\
&\quad 2,1,0,0,1,0,0,1,2,3,4,5,6.7,6,7,8,9,10,11.
\end{aligned}
$$

Figure 9, on the other hand, shows an example of a history where convergence to fictitious play takes place rather quickly. But simplistic learning is able to regain a substantial amount of weight at a later stage of history, and it does so for an extended period[46]: For about 80 days and then again for about 40 days. The *GG* figures for those periods are reported above. Although simplistic learning does not even attain half of the weight its presence is strong enough to let volatility exceed the fundamentals' level.

The mean daily profit now is equal to 12.78 currency units with a

[46]The relevance of the difference between the possible rules for this play, described above, shows up here.

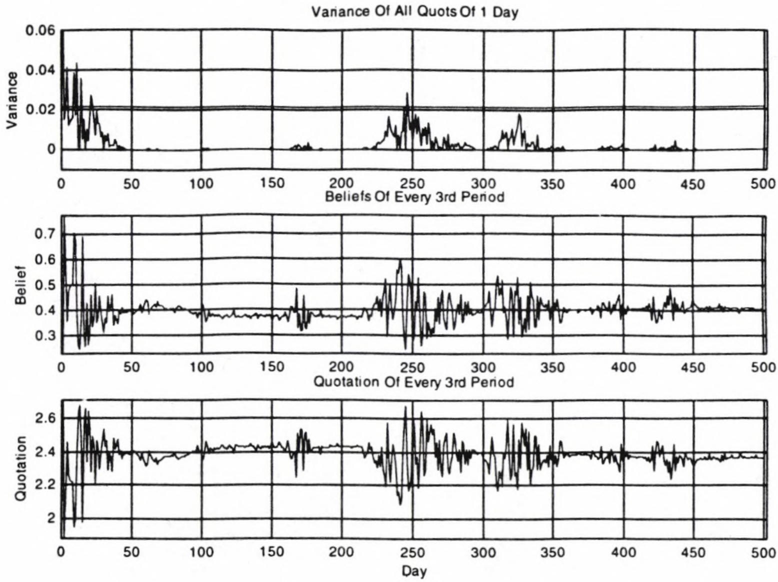


Figure 9:

mean daily spread of 5.3628 compared to the respective hypothetical profit figures of simplistic learning and fictitious play: 9.53 and 12.88 for this simulation run. (The respective spread figures are: 5.5435 and 5.3540.)

Summarizing, there seems to be a gravitational pull towards the pure fictitious play strategy. After a relative shorter or longer period the game always converges to this strategy. However, it is interesting to notice that this convergence does not happen more rapidly, and that with a continuing comparison of strategy performances the process can again move away from this equilibrium. This is surprising because we could see earlier that, favorable to fictitious play, there is a considerable difference in profits between the two learning rules. The explanation for our observation here seems to be the short length of the trading day: In three periods only, with the right sequence of phone calls chance can let the simplistic learning rule be more successful. It will be interesting to see later if and how this outcome changes with a longer trading day.

6.5 Conclusions of the Many-Trading-Days Simulations

While in the previous section the different parameters' impact was analyzed in this section we have looked at the characteristics of different learning rules for the system's long run behavior: Do they lead to a convergence of the quotations' variance and is the eventual convergence result stable?

The outcome strongly depends on the specific learning rule in use: With simplistic learning no convergence is reached at any point of time and the true value of the distribution is never learnt. Even if it were learned at some point the trader would not know and continue to update according to the incoming phone calls. Volatility is high and frequent in this case, and so is excess volatility.

The much smarter updating rule of fictitious play, instead, leads to a rather quick learning of the true distribution and, thus, to a convergence of the mid-rates' variance. Excess volatility is present only for the first couple of days and then drops to *zero*. The convergence result is stable. Furthermore, profits with this learning rule are significantly higher than with simplistic learning.

Evolutionary play, as a play of the previous two learning rules against each other, leads to a convergence with fictitious play being the dominant strategy. However, the convergence result is not stable. This outcome is dependent on the definition of the game, i.e. whether rule comparison continues after convergence or not. For the "mistrust" interpretation that has been used here convergence is not stable. Profits with this learning rule are fairly close to profits with fictitious play. The slight difference in size is due to the "experimental phase" in which strategies are mixed.

6.6 Changes in the Institutional Environment: The Length of the Trading Day

As for implementing a change of the institutional environment a lengthening of the trading day has been chosen: A day now has six rather than three periods. The closed position constraint remains, but there is more information arriving (three more phone calls) which increases the possibility of learning. We are interested to see how this affects the quotations' variability and the learning outcome. First we will analyze how the system's sensitivity changes with respect to its parameters. Then we would like to see whether and how the characteristics of the different learning outcomes change.

For all following simulations the range of parameter value variation has been the same as in the case of the shorter trading day. Results are thus easily comparable.

The Impact of the Size of the Intercept A

Observation 9 *The mid-rates' volatility dependence on the intercept is strongly positive and is slightly bigger than in the shorter trading day setting.*

Excess volatility is throughout positive and increasing in A.

Changing the value of the intercept for a longer trading day setting results in an almost identical graph to the shorter trading day outcome. The increase of the mid-rates' variance is slightly bigger and reaches a value of ~ 1.5 at $A = 5$ as compared to ~ 1.3 in the first simulation. The reason can be found looking at the band of possible sixth period quotations: With a trading day of six periods length the number of

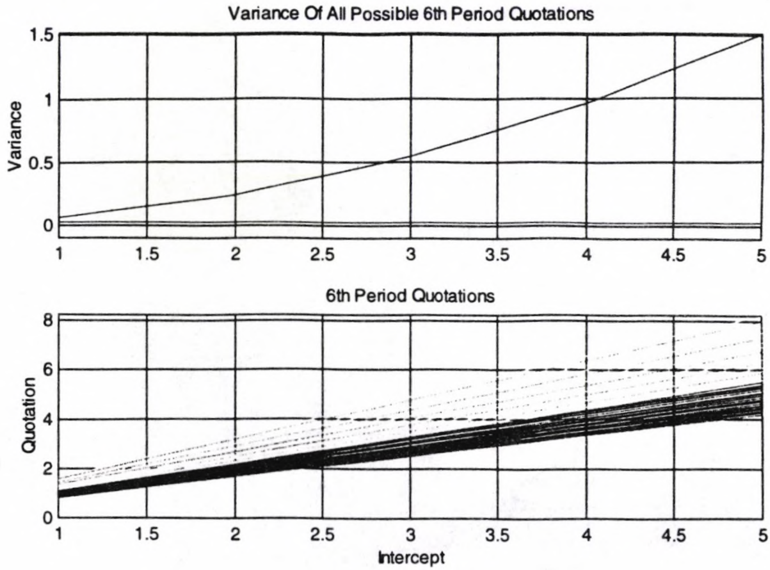


Figure 10:

possible quotations increases to $2^{N-1} = 32$ (where N is the number of periods). The possible quotations' range is slightly bigger than with three periods: At $A = 5$ the range's interval is $[4.2; 8.21]$ compared to the shorter day's interval of $[4.44; 7.41]$.

The Impact of the Size of the HET's Parameter of Price Sensitivity d

Observation 10 *With a longer trading day the impact of HETs' price sensitivity on the mid-rates' variance is being strongly increased.*

Excess volatility is therefore higher and present for higher values of price sensitivity as well.

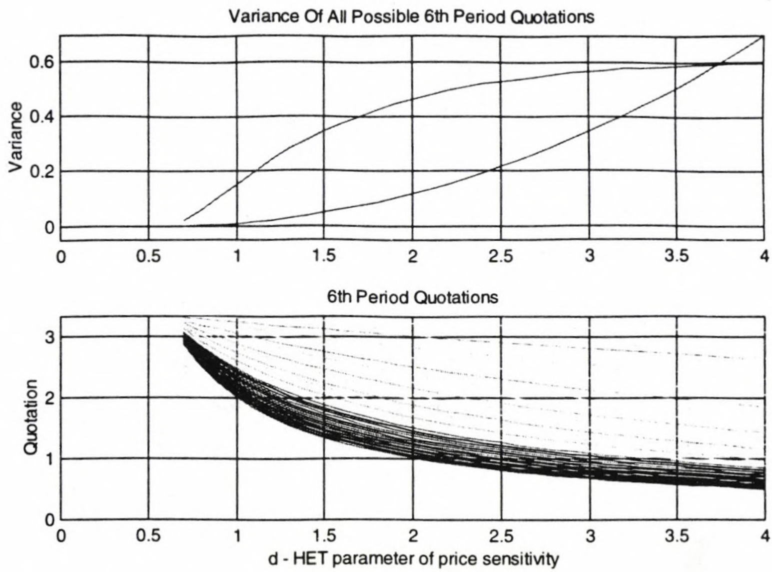


Figure 11:

The band of possible sixth period quotations broadens considerably with a longer trading day: At $d = 4$ they range from 0.5067 to 3.0622 compared to an interval of [0.5594; 1.9512] for the shorter day. With an only minor increase of the mean (from 1.0778 to 1.1152) this leads to a considerable increase in the quotations' variance whose maximum level of excessiveness is now reached with 0.3455 (compared to 0.24 beforehand), more than a 40% increase. Excess volatility begins to become negative at $d = 3.8$ whereas in the shorter day version it did so already at $d = 3.1$.

The Impact of the Size of the LET's Parameter of Price Sensitivity g

Observation 11 *An increased number of trading periods multiplies the parameter's g impact on the variance and, thus, the size of excess volatility.*

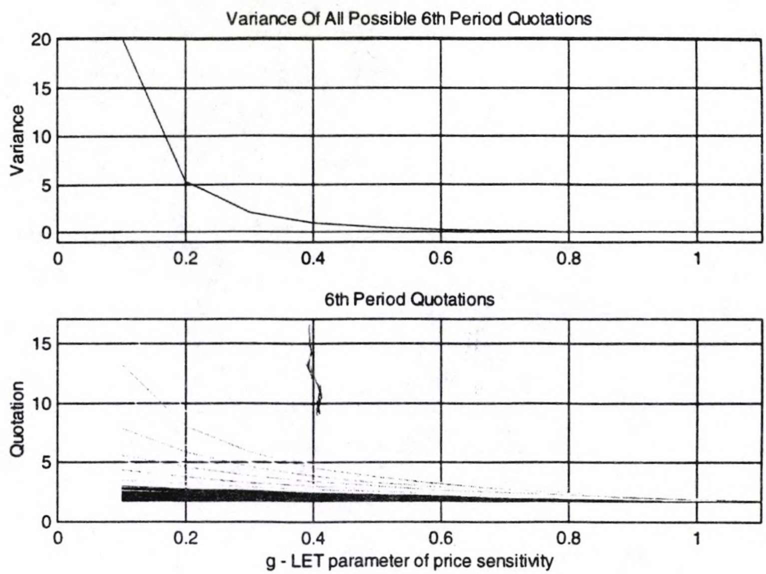


Figure 12:

As in the previous simulation the impact of an increased number of trading periods is a multiplicative one - for the variance as well as for the range of possible quotations. Once again the biggest range of possible quotations is where the distance between the LET and the HET parameter is the highest. But now the range's interval is given by

[1.6909; 17.0667] whereas beforehand it was [1.8824; 8.4211]. The highest quotation possible is more than double as high as was the case for the shorter day. Excess volatility, thus, is initially almost three times higher. This huge difference becomes soon smaller but remains throughout positive.

The Impact of the Size of the Prior Belief $q1$

Observation 12 *The prior's impact on the mid-rates' variance is very small. Excess volatility remains thus positive as before and hardly changes with a changing* $q1$.

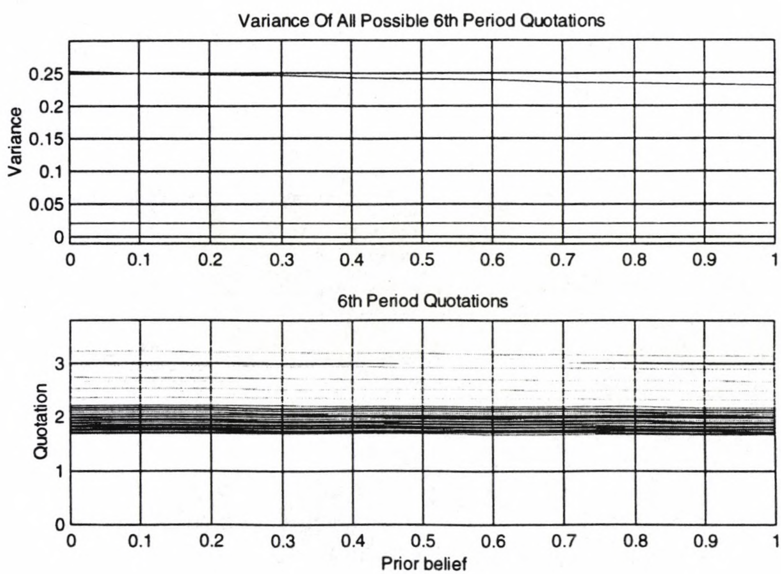


Figure 13:

With a longer trading day the trader's initial belief becomes almost insignificant for the height of volatility and excess volatility: The variance remains around a value of 0.24 which is more or less the average of the variance's possible values during the shorter trading day. This result is not surprising since we saw already then that the trader's specific updating rule leads to a rather quick diminution of initially big differences in possible priors. This effect becomes reinforced with a longer trading day during which more updatings are taking place.

For the same reason also the quotations remain almost invariably, like a straight line, around the same level while the value of the prior is changing.

The Impact of the Real Distribution of the Population v

Observation 13 *The range of possible last period quotations is slightly increased compared to a shorter trading day.*

Volatility of quotations and excess volatility increase considerably. The variance's maximum moved to the left to $v = 0.3$.

Lengthening the trading day once more has the effect of broadening the range of possible last period quotations without changing the mean significantly. Consequently the variance is increasing and with it excess volatility. However, this effect is more strongly present at the left side of the parameter space; after the variance' maximum it starts to diminish, and at $v = 0.7$ it even becomes reversed. The stronger impact at the left side is due to the shifted "skew" of the curve which moved from $v = 0.4$ to $v = 0.3$.

6.7 Conclusions of the Single-Longer-Trading-Day Simulations

All simulations of this subsection show that an increased length of the trading day leads to an increase of mid-rates' volatility and of excess

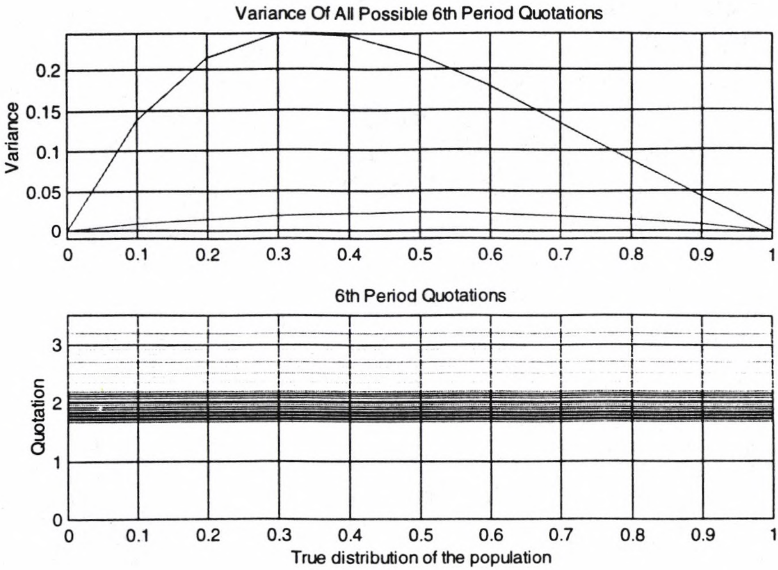


Figure 14:

volatility. The single parameters' role that has been analyzed in the shorter day simulations becomes more pronounced with more periods. The reason for this outcome is the increased number of belief updates which increases the number of possible last period quotations. Those possible quotations are not all observed but they give an indication of the possible range of quotations that can be observed throughout a trading day.

The broader range of possible quotations magnifies the impact every parameter has on the quotations and their variance. Thus, it can be concluded that if a trader does not want to stick to his prior but learn by extracting information from incoming phone calls a lengthened trading day will induce a bigger price variability since more learning results are possible.

The following section which deals with the system's behavior over many trading days will show the impact which different learning rules may have in an institutional setting of a longer trading day.

6.8 Analysis of the System's Long-run Behavior

Our specific interest is to check how convergence behavior of the different learning rules changes with a longer trading day and how the magnitude of the quotations' variability.

The parameter values are the ceteris paribus values of the foregoing simulations. Again, results thus remain easily comparable.

Volatility Behavior and Convergence with simplistic Learning

Observation 14 *With a lengthened trading day the mid-rates' variance tends to be higher and to be higher more often.*

Excess volatility, consequently, tends to occur more frequently and to be higher.

Two typical examples out of a series of one hundred simulations have been reproduced here. At first sight the graphs look rather similar to the ones of a shorter trading day. It can be noticed, however, that negative excess volatility occurs much less frequently: Twice in the first example and only once in the second one (compared to more than *ten* for the shorter day). Furthermore, the maximum oscillations reach more frequently high levels (values higher than 2.5 are reached around $10 - 14$ times compared to around $6 - 9$ times); and they can also reach even higher levels than is the case for shorter days (~ 4.2 in the first example compared to ~ 3.6). With a longer trading day excess volatility is thus often *higher*, and it is so *more often*.

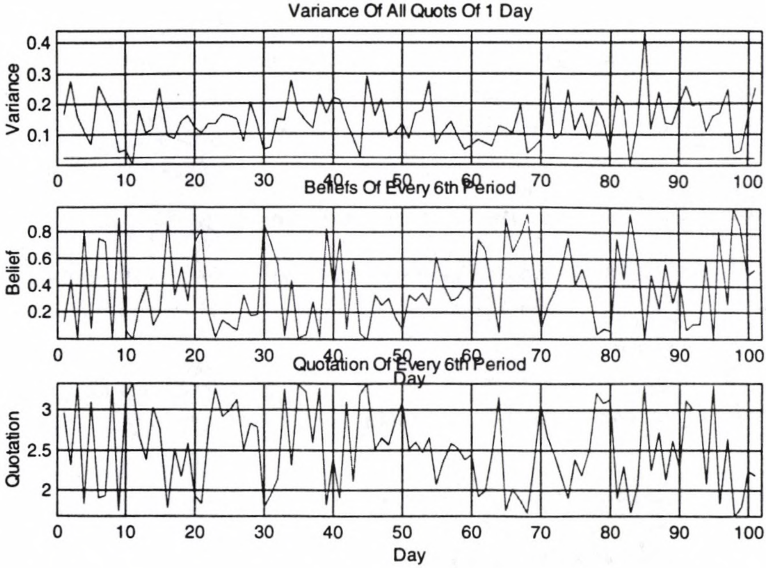


Figure 15:

The range of the quotations and beliefs does not change compared to the case of less periods per day.

Volatility Behavior and Convergence with Fictitious Play

Observation 15 *The speed of learning does not change with a longer trading day.*

Volatility and excess volatility can initially be much higher, but they fall to a size of almost zero at the same speed or even faster.

Another two typical examples have been represented here. In most of the simulations the initial variance was much higher than has been the

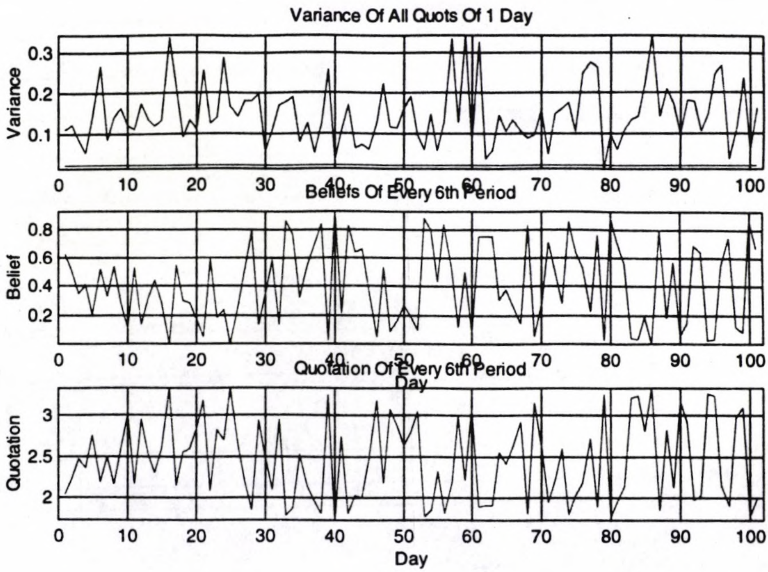


Figure 16:

case for the shorter day. The variance drops then within a few days to a value that is close to *zero*. However, it continues to take on values different from *zero* for a much more extended period of time - up until the 25th to 30th trading day. These two observations can be explained by the longer trading day which increases the number of observable quotations throughout one day: With three more periods there are three more observations influencing the variance. Like this the variance of the first and maybe second day tends to be much higher than has been the case for the shorter day. But the higher number of observations continues to have a visible impact for many more days.

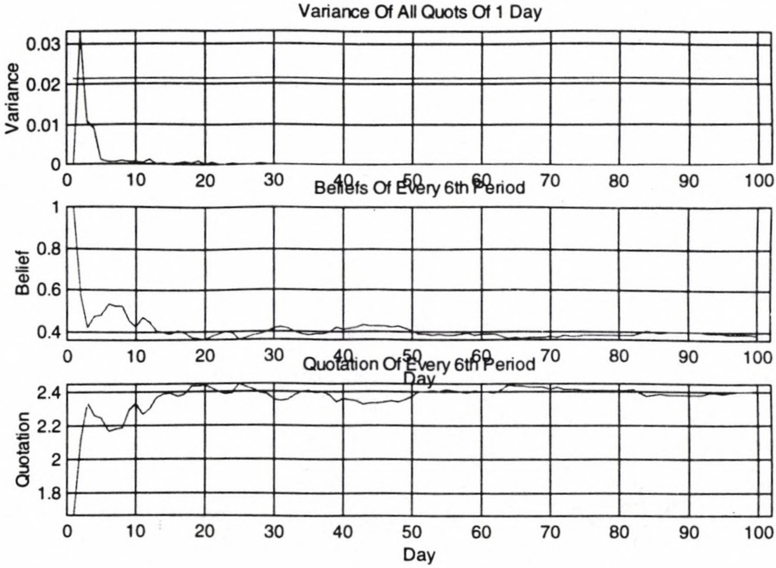


Figure 17:

Volatility Behavior and Convergence with Evolutionary Play

Observation 16 *Compared to the shorter day convergence is reached more quickly and is stable.*

Excess volatility is initially higher when the weight of simplistic learning is still high; it becomes quickly negative with fictitious play dominating.

$$GG = 21, 20, 21, 22, 21, 22, 21, 20, 19, 18, 17, 18, 19, 18, 17, 18, 17, 18, 19, 18,$$
$$17, 16, 15, 16, 17, 18, 17, 16, 15, 14, 15, 16, 17, 16, 15, 14, 13, 12, 11, 12,$$

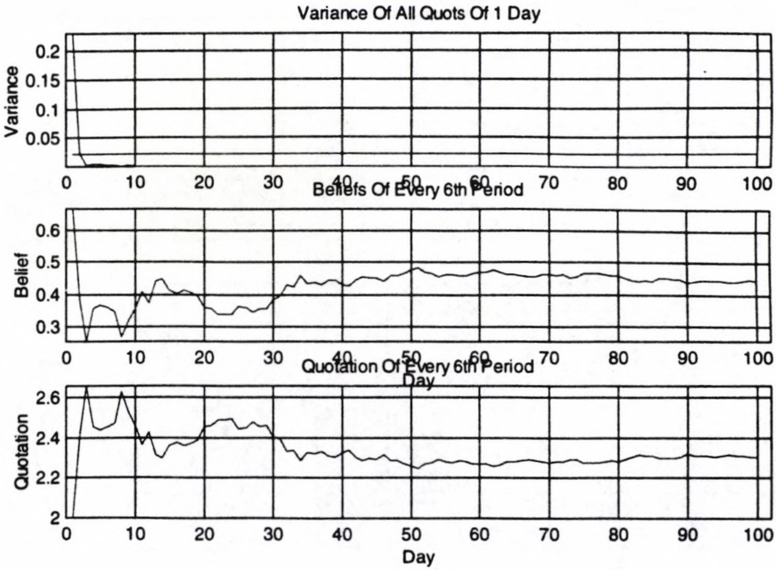


Figure 18:

$$11, 10, 9, 10, 9, 8, 9, 8, 9, 8, 7, 6, 5, 4, 3, 2, 1, 2, 1, 0, 1, 2, 3, 4, 3, 2, 1, 0, 0,$$
$$0, 0, 0, 0, 0, 1, 2, 1, 0, 1, 0, 0, 0, 0, 1, 2, 3, 2, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1.$$

The two cases collected here confirm in some respects our expectations from the respective simulations of the shorter trading day: The learning process converges at a higher speed, and once an equilibrium point has been reached it remains very stable (this can be clearly seen in the second case where there are many "attempts" of simplistic learning to gain more weight but which never succeed to move very far away from a *zero* weight). We relate this outcome to the higher number of periods over which relative performance is being compared. It is thus less

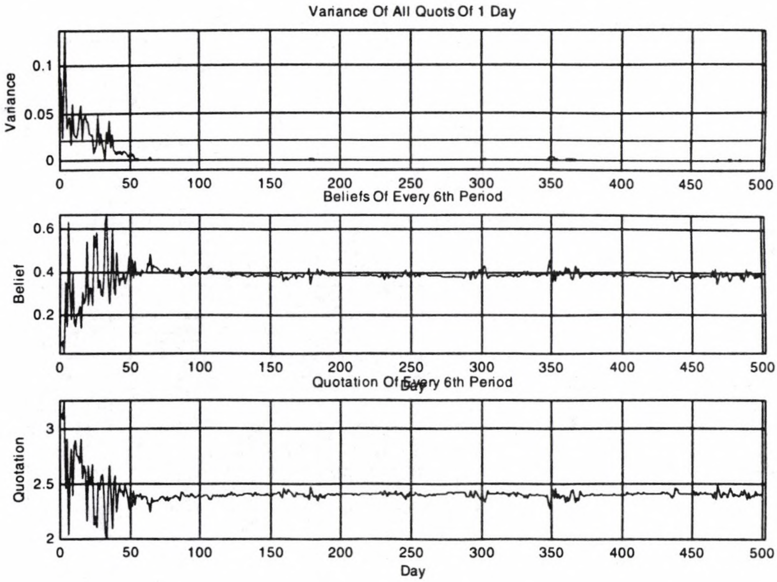


Figure 19:

likely that by pure chance a better performance becomes attributed to the simplistic learning behavior although it simply depends on a lucky combination of phone calls.

But while the foregoing simulations showed a positive impact of the lengthened trading day on the quotations' variance it is not possible to reidentify that outcome here (even comparing the single elements of *GG* and variances of equal weight structure between the shorter and longer trading day). It seems that the increase in volatility due to a higher number of observations is outweighed by the higher speed of convergence towards fictitious play.

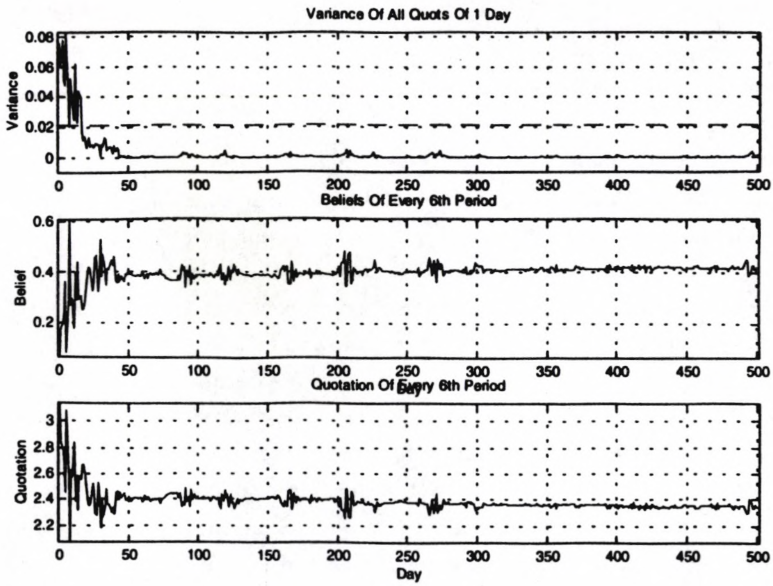


Figure 20:

$$GG = 2,3,4,5,6,7,6,5,6,5,4,3,2,1,0,0,1,2,1,2,$$
$$1,2,1,2,3,4,3,4,3,2,1,0,0,0,0,0,0;0,0,0,$$
$$0,0,0,1,0,1,0,0,1,0,1,0,1,0,0,0,0,1,2,1,$$
$$0,0,1,2,3,4,5,4,3,4,5,4,5,4,3,4,3,2,1,0,$$
$$0,0,0,1,0,0,0,0,0,1,0,1,2,1,0,1,0,1,2,3.$$

(GG is represented for the trading days 200-300.)

6.9 Conclusions of the Many-Longer-Trading-Day Simulations

The foregoing simulations indicate that a lengthened trading day increases the volatility of observable quotations. This result seems obvious for a learning rule which never leads to a converging outcome. It is less obvious, though, for a learning rule like fictitious play that does converge: Here more information arriving through more phone calls in a day should cause quotations to be closer and the variance to be lower. However, this is not the case since the amount of new updates during the first *20-30* trading days causes the quotations to vary more than the learning process does stabilize them. Only from then onwards corrections are so minor that they have practically no impact on the variance any more.

It can be concluded that, depending on the variance definition (all observable quotations throughout a day or throughout a period) it is not recommendable to extend the length of a trading day, or expressed positively: In order to check volatility and excess volatility in the foreign exchange market it may be worth considering a shortening of the trading day.[47]

Summarizing it can be said that as for the highly stylized monopoly case (excess)volatility can be explained with the assumption of simplistic learning behavior. The monopolist will (eventually) use fictitious play as his dominant strategy which can lead to a fairly rapid conversion of volatility to *zero*. Yet initial volatility is very high for a couple of days. Moreover, if we imagine the arrival of new information - something that happens very frequently in the foreign exchange market - the learning process would have to start all over again, exhibiting the same high initial volatility. In other words, in a market with news arrival convergence would most probably not occur such that even with a learning rule like

[47]In our paper on competition in the foreign exchange market (Wuthe (2000)) we will investigate how a change in the institutional setting affects these results when volatility is measured as the variance between quotations of the *same* period.

fictitious play part of the observed excess volatility could be explained.

7 Conclusion

The aim of the foregoing research has been to provide a possible explanation for the commonly observed phenomenon of foreign exchange rate volatility. The main focus of our investigation has been the role that learning and the institutional framework play. Based on work by Zabel (1981) and Suvanto (1993) we have been able to develop a multiperiod model that shows the exchange rate not only as dependent on such parameters as inventory and customers' price sensitivity, but as well on traders' subjective beliefs about some unknown parameter. This, in turn, allows to describe the exchange rate's movement as linked to the trader's learning process over time. In order to be able to possibly reproduce exchange rate patterns that exhibit high or excessive volatility learning mechanisms have been chosen that are suboptimal in terms of learning efficiency. It has been seen in the introductory part that a new strand of research is pursuing the impact of agents that behave less than fully rational. We in our research[48] are able to show that one does not necessarily have to assume some kind of boundedly rational behavior in order to justify the application of rather simple learning mechanisms. On the contrary, they can be a sign of full rationality since their application may allow to seize the relative highest profit.

Regarding the spread and the price our results confirm some findings of the literature (see e.g. Ho and Stoll (1983) and Suvanto (1993)) while adding novel aspects. As in other models the spread shows to be independent of the inventory, with only its placement being affected by the inventory. In our model the spread's independence of the inventory is preserved. But its size changes from period to period due to the belief updating process.- The price which adjusts the inventory towards

[48]This paper together with Wuthe (2000).

an equilibrium level shows the same dependence on traders' updating behavior.

Another key aspect of the market microstructure approach is its concern about the organization of the market. The evolution of prices differs, e.g., between markets where a multitude of market makers simultaneously announce prices and markets where there is a central auctioneer. As an example for the impact of the institutional setting on exchange rate volatility we have chosen the length of the trading day. It has turned out that in an environment with learning (excess)volatility becomes reinforced with a lengthening of the day due to the increased number of updating possibilities. This is true not only applying a measure that takes into account the number of all possible quotations, but also for a measure of the empirical variance. Furthermore, this finding holds as well - for an extended period - for learning rules that do converge over time.

All these results have been shown to depend in specific ways on customers' price sensitivity, the volume of trade, and population's true distribution.

While being a small contribution only with limited scope we are convinced that the here presented research confirms the importance of a market microstructure approach to the problem of explaining the phenomenon of exchange rate volatility.

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Appendix 1: The Solution to the Dynamic Optimization Problem

The monopolist's sequential pricing rule can be obtained by solving the dynamic optimization problem in the following way:[49] We start solving for the optimal quotation and spread of the last period $(T-1, T)$ and proceed then recursively backward in time. The solution to the last period's problem is found by means of the following optimization:

$$\underset{s_{T-1},z_{T-1}}{Max} \quad \{q_{T-1} \cdot \left[A \cdot s_{T-1} + B \cdot z_{T-1} - \delta \cdot \left(s_{T-1}^2 + z_{T-1}^2\right)\right] + \\ (1-q_{T-1}) \cdot \left[A \cdot s_{T-1} + B \cdot z_{T-1} - \gamma \cdot \left(s_{T-1}^2 + z_{T-1}^2\right)\right]\}$$

$$s.t. \qquad 0 = m_{T-1} - E_{T-1}\{m_T\} - A + q_{T-1} \cdot \delta s_{T-1} + (1-q_{T-1}) \cdot \gamma s_{T-1}.$$

[49]The solution follows closely the procedure applied by Suvanto (1993).

and

$$E_{T-1}\{m_T\} = m^*.$$

Differentiating the resulting Lagrangian with respect to the controls s_{t-1}, z_{t-1}, and the multiplier μ_{t-1} and solving the first-order conditions one obtains:

$$\begin{aligned}
s_{T-1} &= \frac{A}{q_{T-1}\delta + (1-q_{T-1})\gamma} - \frac{1}{q_{T-1}\delta + (1-q_{T-1})\gamma}(m_{T-1} - m^*), \\
z_{T-1} &= \frac{B}{2 \cdot (q_{T-1}\delta + (1-q_{T-1})\gamma)}, \\
\mu_{T-1} &= \frac{A}{q_{T-1}\delta + (1-q_{T-1})\gamma} - \frac{2}{q_{T-1}\delta + (1-q_{T-1})\gamma}.
\end{aligned}$$

Optimal spread and mid-rate can be inserted into the expected revenue function which results into the following value of the last-period problem:

$$\begin{aligned}
J_{T-1}[m_{T-1}] &= A \cdot s_{T-1} + B \cdot z_{T-1} - q_{T-1}\left\{\delta \cdot \left[(s_{T-1})^2 + (z_{T-1})^2\right]\right\} \\
&\quad - (1-q_{T-1})\left\{-\gamma \cdot \left[(s_{T-1})^2 + (z_{T-1})^2\right]\right\}.
\end{aligned}$$

Let us now assume that the general solution for the optimal spread and mid-rate at an arbitrary moment t is given by:

$$\begin{aligned}
s_t &= \frac{A}{q_t\delta + (1-q_t)\gamma} - \frac{1}{q_t\delta + (1-q_t)\gamma}(m_t - m^*)/(T-t). \\
z_t &= \frac{B}{2 \cdot (q_t\delta + (1-q_t)\gamma)}.
\end{aligned}$$

so that the value function is equal to:

$$\begin{aligned}
J_t[m_t] &= A \cdot s_t + B \cdot z_t - q_t\left\{\delta \cdot \left[(s_t)^2 + (z_t)^2\right]\right\} \\
&\quad - (1-q_t)\left\{-\gamma \cdot \left[(s_t)^2 + (z_t)^2\right]\right\}.
\end{aligned}$$

Then one only needs to show that the solution of

$$\begin{aligned} J_{t-1}\left[m_{t-1}\right] &= \underset{s_{t-1},z_{t-1}}{Max} \quad \{q_{t-1}\cdot\left[A\cdot s_{t-1}+B\cdot z_{t-1}-\delta\cdot\left(s_{t-1}^2+z_{t-1}^2\right)\right]+ \\ &\quad (1-q_{t-1})\cdot\left[A\cdot s_{t-1}+B\cdot z_{t-1}-\gamma\cdot\left(s_{t-1}^2+z_{t-1}^2\right)\right]\}+E_{t-1}\{J_t[m \end{aligned}$$

at moment $t-1$ results into a spread and mid-rate that give a value function of the same form that has been assumed.- Making use of the explicit form of $J_t[m_t]$ one yields the following optimal mid-rate and spread as a solution to the problem:

$$\begin{aligned} s_{t-1} &= \frac{A}{q_{t-1}\delta+(1-q_{t-1})\gamma}-\frac{1}{q_{t-1}\delta+(1-q_{t-1})\gamma}(m_{t-1}-m^*)/(T+1-t) \\ z_{t-1} &= \frac{B}{2\cdot(q_{t-1}\delta+(1-q_{t-1})\gamma)}. \end{aligned}$$

Inserting these expressions into the value function gives the following expression:

$$\begin{aligned} J_{t-1}\left[m_{t-1}\right] &= A\cdot s_{t-1}+B\cdot z_{t-1}-q_{t-1}\left\{\delta\cdot\left[(s_{t-1})^2+(z_{t-1})^2\right]\right\} \\ &\quad -(1-q_{t-1})\left\{-\gamma\cdot\left[(s_{t-1})^2+(z_{t-1})^2\right]\right\}. \end{aligned}$$

which is indeed of the assumed form.

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